# DEVELOPMENT OF A STRATEGIC COMPLEXITY MANAGEMENT FRAMEWORK FOR INDUSTRIAL SYSTEMS
## - A multi-case study -

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# Abstract

*Today decision-makers face surging increases in overall system complexity leading up to more unstable and unpredictable business environments. Leaders and decision-makers are confronted with volatility (dynamic and intense changes), uncertainty (lack of predictability), complexity (interconnection of parts which is sometimes overwhelmingly difficult to process), and ambiguity (unclear relationships), namely the VUCA-world.*

*The implications of the VUCA-world for business and strategy can be applied to the rise of complex cyber-physical systems in Industry 4.0. There is an expressed need to develop complexity management frameworks that integrate different individual measures of dealing with industrial system complexity into a synergetic strategic framework.*

*In this regard new frameworks that reflect "real-life complexity" of industrial systems and their practitioners are being called for.*

*It is therefore the core aim of the thesis to develop and apply a strategic complexity management framework (SCM) that fits in the individual reality of the decision-making practitioner by integrating different complexity dimensions of industrial systems in a holistic, synergetic, and strategic way.*

*As a starting point for achieving this aim, an investigation and exploration of relevant theoretical frameworks is conducted and accumulates in the proposition of a set of hypotheses H1-H13 as an explanatory approach to achieve a multi-dimensional definition of industrial system complexity and to explore its impact on decision-making based on information growth in industrial systems.*

*In a second step, H1-H13 are applied to develop a theoretical complexity space model for industrial systems. In the model the static and dynamic complexity of an industrial system are integrated in a complexity space modelling approach, where information complexity boundaries expand over time in a static compound space of a system and serve as an indicator for system instability in a static complexity space.*

*The capabilities of the complexity space model are theoretically demonstrated, alongside a set of assumptions concerning the behavior of industrial system complexity. The developed complexity space model represents the core theoretical foundation for the establishment of the SCM in a third step.*

*In the third step the complexity of an industrial system is captivated via the strategic complexity management framework (SCM) in the form of a strategic 8- quadrant matrix in adherence to the axioms of the paradigm of strategic complexity engineering which are to acknowledge, characterize, anticipate, and manage complexity.*

*Definitions of static, dynamic and environmental conception of complexity of industrial systems are holistically integrated to capture the internal and external strategic management perspective in the SCM framework and the strategic capabilities of the SCM framework are theoretically demonstrated based on a set of generic norm strategies.*

*In a fourth step the SCM is applied for strategic complexity management purposes to four different real-world cases of industrial manufacturing systems with the goal to test, explore and discuss the practical decision-aiding applicability of the framework via an interventionistic multi-case study based on qualitative document review.*

*The individual results of the SCM application on the four different cases are described and discussed.*

*Key-learnings across cases are identified and discussed as a conclusion.*

*Finally, a research outlook is provided.*

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*In loving memory of Hermann Freund, Maria-Elisabeth Pfeiffer and Dr. Günther Pfeiffer.*

*How you approached the challenges of life will always be an example to me.*

*How exquisitely the individual mind*

*(And the progressive powers perhaps no less*

*of the whole species) to the external world*

*is fitted*

*and how exquisitely, too (…)*

*The external world is fitted to the mind*

*And the creation (by no lower name*

*can it be called) which they with blended might accomplish:*

*This is our high argument.*

***William Wordsworth***

# Table of contents

# List of tables

# List of figures

# List of abbreviations

**VUCA:** Volatility, Uncertainty, Complexity, Ambiguity

**CPS:** Cyber-physical system

**CPSS**: Cyber-physical system of systems

**CHS:** Cyber-human system

**H(S):** Entropy of a system

**IKTF:** Industry 4.0 Knowledge and Technology Framework

**H1 -HX:** Hypotheses H1 – HX

**SCM:** Strategic complexity management framework

**SMTT:** Strategic management tools and techniques

**S:** System

**CAS:** Complex adaptive system

**BCG:** Boston Consulting Group

**SWOT:** Strength, Weaknesses, Opportunities, Threats

**AI:** Artificial intelligence

**NN:** Neural network

**SRQ:** Sub-research question

**MRQ:** Main research question

**O1-OX:** Research objective O1-OX.

**SR:** System regulation

**D:** Disturbance

**R:** Regulatory response

**X:** Choice set

**O:** Outcome

**C:** Complexity

**V:** Volume

**U:** Utility

**EU:** Expected utility

**M:** Macro development level

**F:** Framework level

**I:** Integration level

**IoT:** Internet of Things

# 1 Introduction

Today decision-makers face surging increases in volatility, uncertainty and overall business complexity leading up to more unstable and unpredictable business environments. Leaders and decision-makers are confronted with volatility (dynamic and intense changes), uncertainty (lack of predictability), complexity (interconnection of parts which is sometimes overwhelmingly difficult to process), and ambiguity (unclear relationships), which accumulate in the so-called VUCA-world. (Krawczyńska-Zaucha, 2019)

Even though individual VUCA aspects on their own can already lead to overwhelming challenges, a combination of VUCA aspects or the presence of all four combined can lead to complex business problems that are nearly unsolvable for decision-makers. (Milar et al. 2018)

The components of the VUCA-world thus represent the main four challenges for doing sustainable business and designing strategy in the modern business world.

They are consequently adopted by business leaders and decision-makers to describe and address the rapid changes of the business environment and to capture and benefit of overcoming challenges and newly arising opportunities. (Krawczyńska-Zaucha, 2019, Milar et al. 2018)

In the context of industrial systems, the implications of the VUCA-world for business and strategy can be applied to the rise of Industry 4.0 and cyber-physical systems (CPS). CPS represent new and complex systems or system environments, in the form of cyber-human systems (CHS) or cyber-physical systems of systems (CPSS), that combine the potentials of physical artifacts, humans and industrial systems due to integrated computational and physical capabilities. (Törngren & Sellgren, 2018)

CPS are established to produce a global intelligent behaviour featuring autonomy, self-control and self-optimization and are expected to be a decisive driving force for advances in different areas in manufacturing, opening new areas of innovation. In contrast to the potential of CPS for manufacturing it is well understood that current and more traditional manufacturing and industrial systems are already stretching the limits in terms of the development of cost-efficient and trustworthy systems. (Pilloni, 2018, Xu & Ling, 2018)

This urgent matter is additionally amplified by the circumstance that current CPS system design already is unable to support the level of complexity, scalability, security, safety, interoperability, and flexible design and operation that will be required to meet future needs. (Törngren & Grogan, 2018)

The line of argument makes visible that it is now imperative for industry decision-makers to obtain practical methods and tools of strategic planning addressing the management of complex industrial systems, like CPS, thus aiming to solve the challenges of the volatility, uncertainty, complexity, and ambiguity. (Knyazeva, 2020, Törngren & Sellgren, 2018)

As demonstrated by the research of Freund et al. and Freund & Al-Majeed (2021d, 2021e, 2021f) one option to achieve this are holistic strategic management frameworks in the form of strategic management tools and techniques (SMTT) dedicated to practical strategic complexity management.

The mentioned aspects now form the central motivation of the thesis to showcase the development and application of a novel SMTT for strategic complexity management for industrial systems in the form of the SCM.

To achieve this the thesis now follows the following structure:

As a first step *Chapter 2* introduces the core topics of the theoretical background of this thesis. Thus, the most relevant key-definitions of Industry 4.0 in the context of industrial systems are defined in the form of the terms Industry 4.0 itself, technological change, CPS and smart manufacturing.

In *Chapter 3* a structured literature review and analysis of Industry 4.0 and how it manifests complexity is established via the Industry 4.0 Knowledge and Technology Framework (IKTF). The IKTF represents a systematic and analytical approach to the introduced key-terms of Industry 4.0 and the relevant literature and provides a structured approach to Industry 4.0 on a micro-meso-macro level. The IKTF shows how different levels of Industry 4.0 can be assumed to be connected and how Industry 4.0 manifests complexity.

In this light *Chapter 4* now introduces the topic of complexity in the context of industrial systems. An overview over the terms complexity science, the process of defining complexity, scientific models based on complexity science and the concept of emergence is provided.

*Chapter 5* introduces and defines the concept of manufacturing complexity. It establishes a set of definitions of complexity symptoms and complexity assessment methods in industrial manufacturing systems. To achieve this, an overview of the current body of literature is provided in the areas of complexity types, complexity symptoms and complexity assessment methods.

*Chapter 6* now describes the concept of strategic management, complexity management and illustrates and compares four different complexity management frameworks. The addressed research gap in form of a strategic gap in complexity management frameworks is identified.

*Chapter 7* establishes a description of the research aim, four research objectives O1-O4, the main research question (MRQ) and the corresponding four sub-research questions (SRQ1-SRQ4).

As a next step, *Chapter 8* introduces the chosen research philosophy and research methodology in the form of interventionism, decision-aiding and case study research and provides a paradigm for the establishment of strategic complexity management framework.

*Chapter 9* introduces a detailed analysis concerning the nature of complexity as an emerging phenomenon in complex industrial systems and its impact on the decision-making process. It establishes thirteen hypotheses (H1-H13) concerning the nature of complexity and the implications of complexity on the decision-making process in complex industrial systems.

Based on H1-H13 *Chapter 10* introduces a novel conceptual complexity space-based approach to model, quantify and visualize the complexity of modern and future industrial systems in a way that supports the visualization and potentially simulation of the complexity of both the physical and the informational system layers and their respective information flow in a three-dimensional complexity space model.
Building upon the previous achievements *Chapter 11* presents the strategic complexity management (SCM) framework and how it works in terms of structure and functions.

*Chapter 12* provides the description and discussion of the dedicated SCM case study method for the application on real-world industrial systems based on the overall methodology of this thesis. The goal of this chapter is to methodologically allow the exploration and investigation of the practical applicability of the SCM framework on real-world industrial systems. To achieve this the SCM framework is executed four times as a decision-aiding tool, resulting in four individual case studies of real-world industry systems.

As a final step, *Chapter 13* concludes with the presentation and discussion of SCM case study results based on the four case studies. Each case study is presented individually and general key-learnings concerning the application of the SCM on real-world systems are obtained and discussed as the final conclusion to this study.

After introducing the structure of this thesis, Chapter 2 now describes and discusses the topic of Industry 4.0 as a thematic starting point.

# 2 Industry 4.0

This chapter introduces the core topics and definitions of industrial manufacturing in the context of Industry 4.0 industrial systems. For the purpose of this thesis the term *industrial system* shall define any manufacturing, productive system that contributes to the establishment of marketable products and thus to industrial economic value creation. (Rojko, 2017)

Industry 4.0 is a manufacturing approach based on the integration of emerging technologies in the business and manufacturing processes to achieve superior production capacities. The technical aspects of the requirements of a successful integration are primarily addressed by the application of the concepts of cyber-physical systems (CPS). (Rojko, 2017, Pilloni, 2018)

Any Industry 4.0 concept is therefore based on the connections of autonomous CPS building blocks. The CPS blocks are potentially heterogenous embedded systems equipped with intelligent, decentralized control and advanced connectivity. These blocks have the central ability to collect and exchange real-time information with the goal of monitoring and optimizing the production processes. (Rojko, 2017, Pilloni, 2018, Savastano et al., 2019, Roblek et al., 2016)

The technologies introduced by Industry 4.0 thus enable autonomous intelligent communication and cooperation among CPS, so that a higher level of intelligence, and therefore a higher level of flexibility and performance, can be achieved in industrial manufacturing processes. Industry 4.0 is thus assumed to enable three core aspects namely digitization of production, automatization of production and intelligent data interchange. The concept of Industry 4.0 requires a converging combination of digitized, intelligent systems of production through the means of emerging enabling technologies primarily in the form of CPS, Internet of Things and cloud computing. (Rojko, 2017, Pilloni, 2018, Xu & Ling, 2018, Morraret al., 2017, Savastano et al., 2019, Roblek et al., 2016)

The concept of Industry 4.0 therefore represents, in theory, a transformative, evolutionary advancement via technological change from traditional embedded industrial systems in manufacturing to smart industrial production systems defined by autonomous, interconnected CPS. This transformation is expected to allow the successful change from a more standardized mass-production system to a customizable, flexible, cost-efficient and demand responsive production that can efficiently fulfil the requirements of volatile market environments. (Rojko, 2017, Pilloni, 2018, Savastano et al., 2019, Roblek et al., 2016)

Even though the vision and the concept of Industry 4.0. are already well-described on a theoretical level, several unsolved challenges on the technological, integrative, and general level of understanding remain to be better understood and captivated. (Savastano et al., 2019, Roblek et al., 2016)

These challenges effectively inhibit a successful integration of the concept of Industry 4.0 in applied manufacturing systems and that until now, only a limited number of companies achieved performance increases through the integration of aspects of Industry 4.0. (Roblek, et al., 2016)

It can therefore be concluded that the concept of Industry 4.0 while still not fully developed, is ambiguously connected to a variety of other meta-concepts or sub-concepts, like VUCA environments. (Gimpel & Röglinger, 2015)

It is also made evident that the evolution and integration of Industry 4.0 is based on the underlying technological trends, manifested by technological change. Therefore, the next section expands on this.

## 2.1 Technological change

The term technological change describes a positive transition of a system from a technological level to a more advanced technological level in a transition time period. If the transition time periods between a series of technological levels decreases in an exponential manner, exponential technological change can be identified. (Bongomin et al., 2020)

The transitioning from a technological level to a more advanced technological level shall furthermore encompass the emergence of new and more potent technologies, like more productive and efficient tools, facilities, or services (for example robotics or the internet) and the diminishment of less potent technologies. It also contains the habitual and institutional adjustments conducted by the society employing and interacting with the technologies. (Hochwallner & Ribeiro, 2018, Bongomin et al., 2020)

It shall therefore be assumed that technological change can be regarded for a company as a main impact factor of corporate structural change responding to external market incentives that drive competition and economic growth.

According to the research conducted by Bongomin et al. (2020), Industry 4.0 is being driven by exponentially growing disruptive technologies that inaugurate changes at a nonlinear pace, leading to exponential technological change. These emerging technologies have a potential to cause broader societal transformation by changing the existing economic sectors, tenets of work, production, and consumption. This is leading up to Industry 4.0 differing in speed, scale, complexity, and transformative power as compared to the previous industrial revolutions. In general, two types of technologies can be differentiated:

- **Sustaining technologies:** have a constant or incremental rate of improvement of existing customers.
- **Disruptive technologies:** create disruption on the status quo as it produces a unique set of values.

The major implication of disruptive technology is the demand for new course content, employment, knowledge, and skills. (Bongomin et al., 2020) As one central example for a simultaneously sustaining and disruptive technology CPS can now be introduced.

## 2.2 Cyber-physical systems

A CPS can now be described as a new generation of systems emerging from technological change that blend the knowledge of physical artifacts and industrial engineered systems due to integrated computational and physical capabilities. CPS are established in order to produce a global intelligent behaviour featuring autonomy, self-control and self-optimization and are expected to be a decisive driving force for advances in different applicative domains including manufacturing control and for opening up new areas of innovation. (Horvarth & Gerritsen, 2012, Schiliro, 2017)

CPS are characterized by advanced connectivity that ensures real-time data acquisition from the physical world and information feedback from the cyber space and intelligent data management, analytics and computational capability that constructs the cyber space. (Lee & Bagheri, 2015)

CPS are also connected with high system complexity and contains an inherent trade-off relationship between the drawbacks of complexity and the performance increases gained. (Törngren & Sellgren, 2018)

A cyber-human system (CHS) means that humans have an increasingly interconnected relationship with digitized and digital systems and represents an integral factor to establish a functioning CPS. This development is exemplified in the increasing human-machine interaction through new computer systems, the internet, mobile devices, improved sensor technology and possible future applications like brain-machine interfaces and leads to human lives and decision-making increasingly merging with complex technology. (Gimpel & Röglinger, 2015, Horvarth & Gerritsen 2012)

For the purpose of these thesis, the term CPS shall encompass the concept of CHS, if not mentioned otherwise.

Figure 1 now illustrates the general concept of CPS, as shown in Freund & Al-Majeed (2020a).

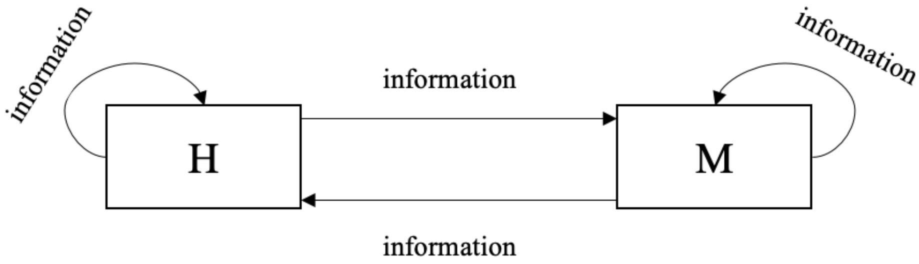



*Figure 1: CPS example*

Figure 1 shows that an exemplary CPS architecture can be described as a closed loop heterogeneous system of a constellation of machine (M) and human (H) units with data interaction enabled through a reflexive and irreflexive multi-directional information flow with a shared data pool.

As a result, the illustrated structure of a CPS is characterized by highly interconnected constellation of heterogeneous agent types situated in reinforcing information diffusion and generation feedback loops.

### 2.2.1 Technologies associated with cyber-physical systems

In a more practical context, cyber-physical manufacturing can now be understood as the utilization and integration several high-tech technology platforms, for example in a smart factory context. Based on the research of Juhas & Molnar (2017), Bongomin et al. (2020) and Andronie et al. (2021) it is now possible to introduce the following technology platforms associated with cyber-physical systems as the following:

- **Advanced (autonomous) robotized production lines:** Modern automated and robotized production lines maximize efficiency, modern technology, accuracy, and speed of production are an essential element in the implementation of CPS.
- **Autonomous supervisory/service mobile units (drones with camera system or handlers to carry light objects):** Drones are easy to use as independent mobile

supervisory units (equipped with a camera) or as highly mobile transport units with the appropriate equipment for the transfer of objects.

- **Industrial 3D printing:** Technology of 3-dimensional printing (additive manufacturing) can provide a high degree of efficiency and variability in the production of a wide range of products. By creating 3D objects based on data from materials such as plastic or metal, it is possible to create complex, easily customizable products whose design is impossible to carry out with classic production techniques.
- **Autonomous traffic units (autonomous carts and manipulators):** Ground handlers and vehicles for transporting heavy loads are forming a connection between the individual modules of CPS.
- **Intelligent management and control system:** Central management and control of all production processes and units must be implemented in such a way as to eliminate the possible errors in the management of complex and time-dependent production processes. This presupposes the exclusion of classical control centres with human service.
- **Distributed communication systems, sensor networks, Internet of Things:** All objects in the production process must communicate with the control system wirelessly. Together with the sensor system they create an information data network. Based on data, the central management system can analyse production procedures and processes and optimize them to achieve greater production efficiency.
- **Augmented operator:** The physical capabilities of human staff can be improved using an additional technical solution, for example exoskeletons.
- **Energy-efficient production:** Utilization of renewable energy sources such as solar panels, energy passive buildings or recycling of raw materials.

To provide further illustration, the manifestation of Industry 4.0 is often exemplified through the concept of a smart factory.

The next section now introduces the smart factory / smart manufacturing approach as a macro-level concept to apply CPS in an Industry 4.0 manufacturing context. (Nagorny et al., 2017)

Consequently, the next section now briefly describes the concept of a smart manufacturing systems or smart factory.

### 2.2.2 Smart factory / smart manufacturing

Smart manufacturing systems are largely autonomous, non-hierarchical physical and logically capsulated systems based on the Industry 4.0 concept that form a complex manufacturing ecosystem. These systems are often summarized under the term smart factory. Smart factory systems are heterogeneous, loosely coupled, cyber-physical systems that again accumulate in a cyber-physical system architecture, a cyber-physical system of systems (CPSS). (Mittal et al. ,2019, Gaham et al., 2013)

Smart factories use information to continuously maintain and improve performance and can be expected to be producing a high variety and volume of data due to the interconnected nature of the contained CPS. (Mittal et al., 2019)

Traditionally, manufacturing was defined as a sequence of processes through which raw materials were converted into finished goods for a fixed market. Smart manufacturing aims to integrate the properties of self-assembly to produce complex and customized products to exploit the new and existing markets. (Gaham et al., 2013)

Figure 2 now illustrates the basic composition of a smart factory**.**

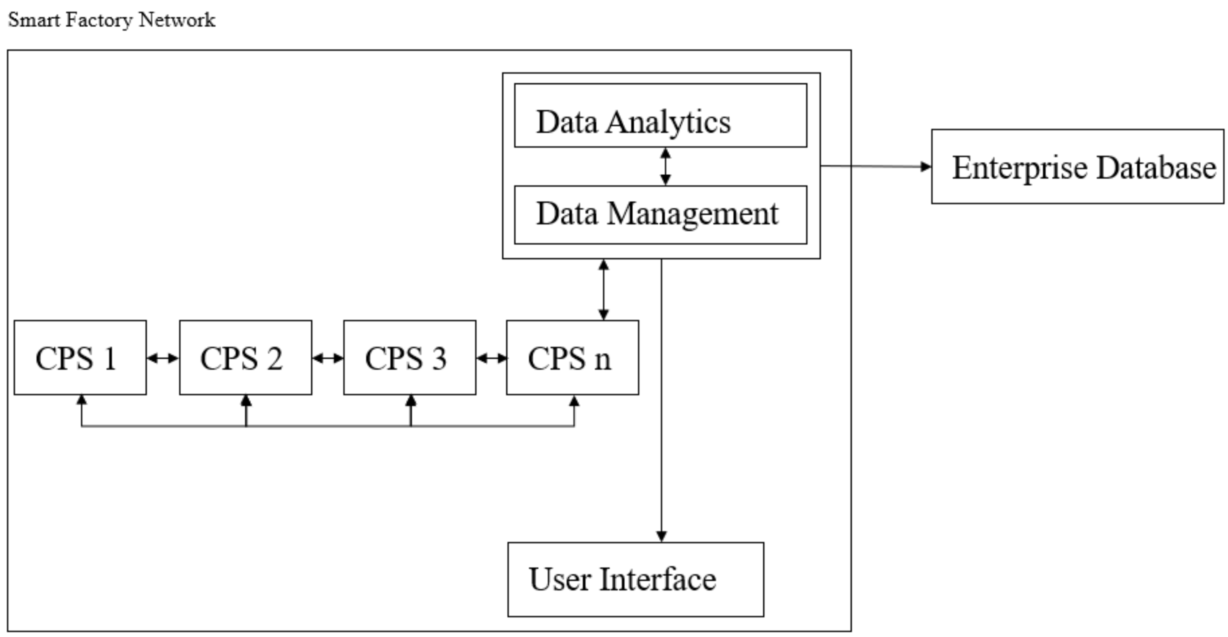



*Figure 2: Smart factory composition*

In an abstracted way, a smart factory network consists out of several interconnected CPS which are connected to the data analytics and data management centre of the factory. The data analytics and data management centre are now connected to the user interface and the system external enterprise database.

It can be shown that the topic of Industry 4.0 combines a wide variety of converging and interconnected concepts and technologies, like the smart factory approach, and challenges the traditional understanding of manufacturing due to merging formerly separated application layers in a monolithic production system into a highly interconnected, decentralized and dynamic system. (Trunzer et al., 2019)

After introducing the first set of relevant concepts and key-terms to achieve a coherent basic level understanding, these can now be applied for the introduction of a more systematic and analytical approach to the literature body in the form of the Industry 4.0 Knowledge and Technology Framework (IKTF) developed by Freund & Al-Majeed (2020,2021).

The IKTF is now described in detail in the next chapter to provide a structured view on Industry 4.0 and how Industry 4.0 manifests complexity.

# 3 Industry 4.0 and the manifestation of complexity

The now introduced Industry 4.0 Knowledge and Technology Framework represents a systematic and analytical approach to the introduced key-terms of Industry 4.0 and the relevant literature and provides a structured approach to Industry 4.0. It shows how different levels of Industry 4.0 can be assumed to be connected and how complexity manifests as a result.

As argued by Camarinha-Matos et al.  (2017) and Jäger et al. (2016), the concept of Industry 4.0 has turned into a buzzword and an “everything fits” catalyser for various technologies and manufacturing approaches.

The everything fits mentality, making the concept of Industry 4.0 difficult to understand, is additionally supported by companies and their respective managers utilizing their own descriptions and concepts, leading to a decreased diffusion of best practice methodologies. (Camarino-Matos et al., 2017)

The presented Industry 4.0 Knowledge Framework (IKTF), as shown in the research of Freund et al. (2020c, 2021d), now wants to avoid an “everything fits” approach for this thesis and is based on the concept of the micro-meso-macro analysis framework and consequently is representative for the approach of micro-meso-macro analysis in managerial practice. (Dopfer et al., 2004)

Based on this aim, the applied core concepts of the IKTF are now illustrated in Figure 3.

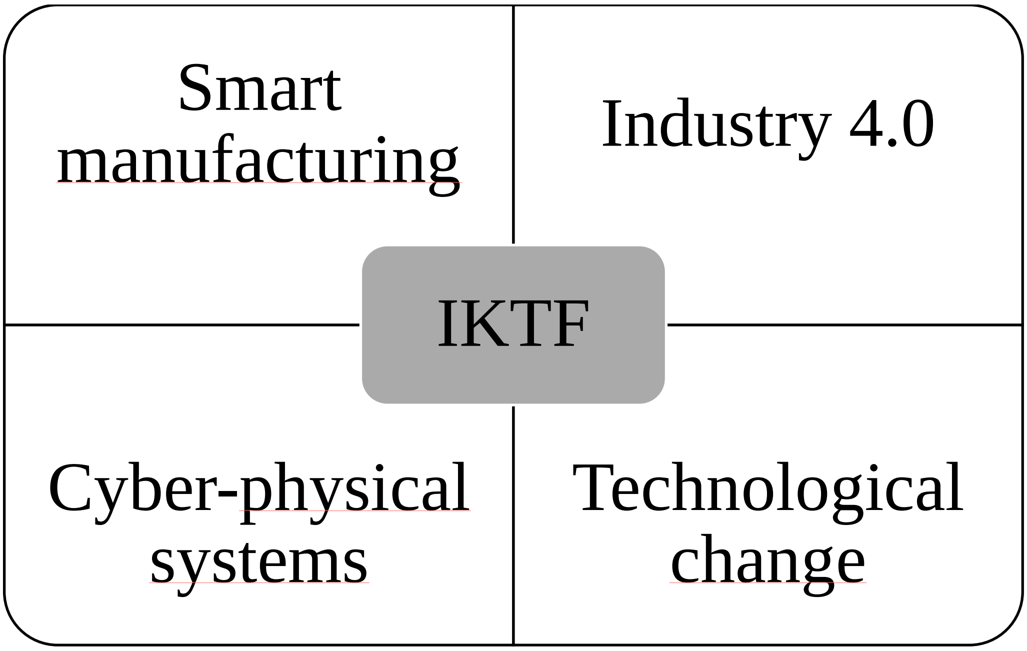



*Figure 3: IKTF core concepts*

As shown, the already defined core-concepts of IKTF, Industry 4.0, Smart Manufacturing cyber-physical systems, cyber-human system and technological change now provide a basis for the introduction of the micro-meso-macro analysis approach of the IKTF in the next section.

## 3.1 Micro-meso-macro analysis

The micro–meso–macro analytical framework represents a proven method of analysis in the social sciences and economics and can greatly enhance the focus, clarity and strength of decision quality in many decision-making and analysis contexts. (Serpa & Ferreira, 2019)

It proposes three categories of factors and places them in three basic levels layering them on top of each other. The macro-level includes the financial, political and sociocultural factors that influence Industry 4.0. The meso-level includes the technical and organizational factors.

The micro-level refers to individual factors, particularly individual companies' intention to use Industry 4.0 in practical economic contexts. This framework is useful in that it affords insight into the various factors that influence the integration and usage of Industry 4.0. It is also suggested that there is interaction between, and interdependence of the different factors. (Serpa & Ferreira, 2019, Dopfer et al., 2004) The micro-meso-macro approach also has seen application in the complexity science and complexity analysis, as shown by the research of Commendatore et al. (2017).

The applied micro-meso-macro framework is an adaption of the model is now illustrated in Figure 4.

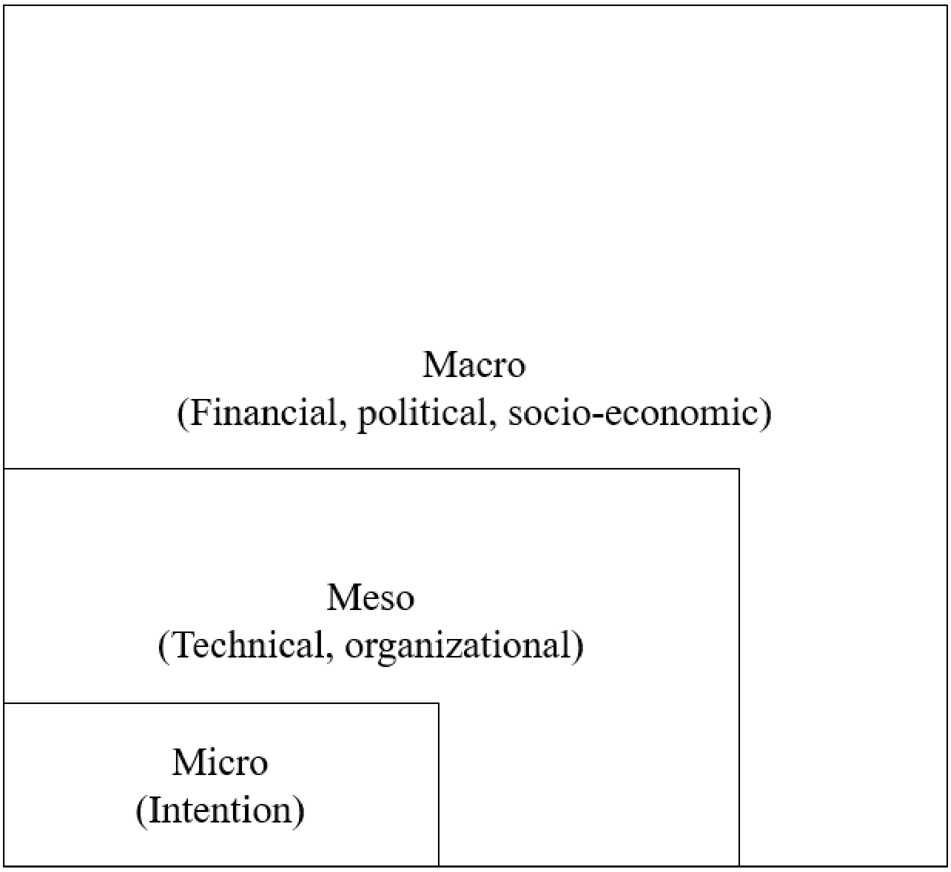



*Figure 4: IKTF micro-meso-macro analysis*

Figure 4 shows, that change is the defining property of macro (i.e., the origination of new rules and the technological dynamics), and coordination occurs as micro and meso structures adapt and change according to or in combination with the macro-level dynamics.

This makes visible that the micro level refers to the individual carriers of rules and decision makers in the organization and the systems they organize, and the macro level consists of the aggregated effect of the system dynamics of the meso level.

The micro level is thus positioned between the elements of the meso, and the macro level is positioned between meso elements. (Dopfer et al., 2004)

Based on these notions, the next section now introduces the IKTF.

## 3.2 Industry 4.0 knowledge and technology framework (IKTF)

The IKTF can now be introduced and is based on the described concept of the micro-meso-macro analysis framework. This is presented in Figure 6.

Figure 5 now illustrates the basic structure of the IKTF.

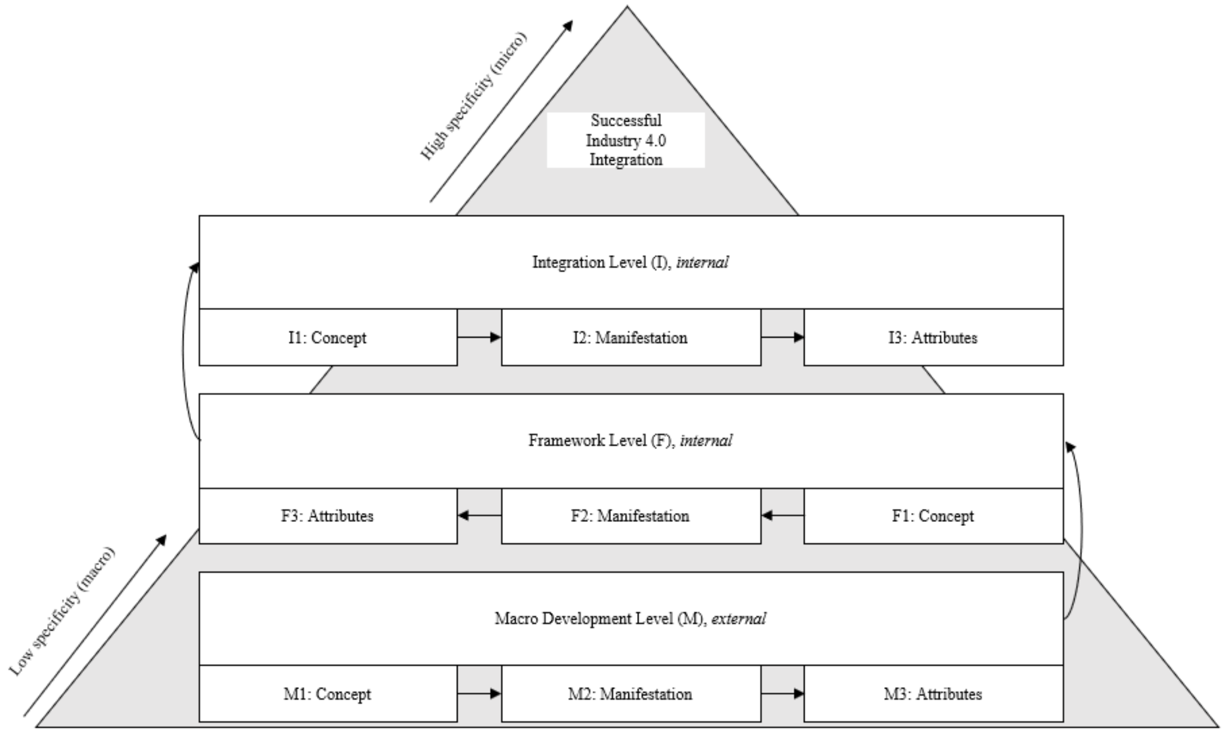



*Figure 5: IKTF basic structure*

Figure 5 shows, that the basic structure of the IKTF follows an inverted micro-meso-macro logic in which the macro-development level (M) is positioned at the bottom, followed by the meso level in the form of the framework level (F) and the micro level in the form of the integration level (I) at the top with transition indicators between each level.

Each level follows the three-step (M1-M3, F1-F3, I1-I3) one-directional logic of displaying the most relevant Industry 4.0 concept for this level, followed by the resulting technological manifestations and the specific attributes in the form of socio-economic and technological impacts for the level.

When the level internal logic chain ends a transition to the next level is implemented, as indicated by the arrows. It is also shown that the transition from (M) to (F) implicates a transition from the company external macro-environment to a company internal perspective, while (F) to (I) remain company internal.

The external environment consists of an organization's external factors that affect its business operations in an indirect manner. Thus, the organization has no or little control over these factors. That means the external environment is generally assumed to be non-controllable and represented by (M).

The internal environment describes forces or conditions or surroundings within the boundary of the organization represented by (F) and (I). The internal environment includes all assets contained within the boundaries of the organization.

Some of these assets are tangible, such as the physical facilities, the plant capacity technology, proprietary technology, or know-how; some are intangible, such as information processing and communication capabilities. Consequently, decision makers can only use company internal assets in (F) and (I) as resources to make decisions in response to (M).

In a next step, all IKTF levels are presented and described in more detail.

### 3.2.1 Macro development level

The Macro Development Level (M) shall be defined as the larger and abstract level of understanding that stands above the other two levels of the framework.

As already mentioned, (M) represents the company external world and the trends that impact Industry 4.0. (M) shall now be defined as the following level structure.

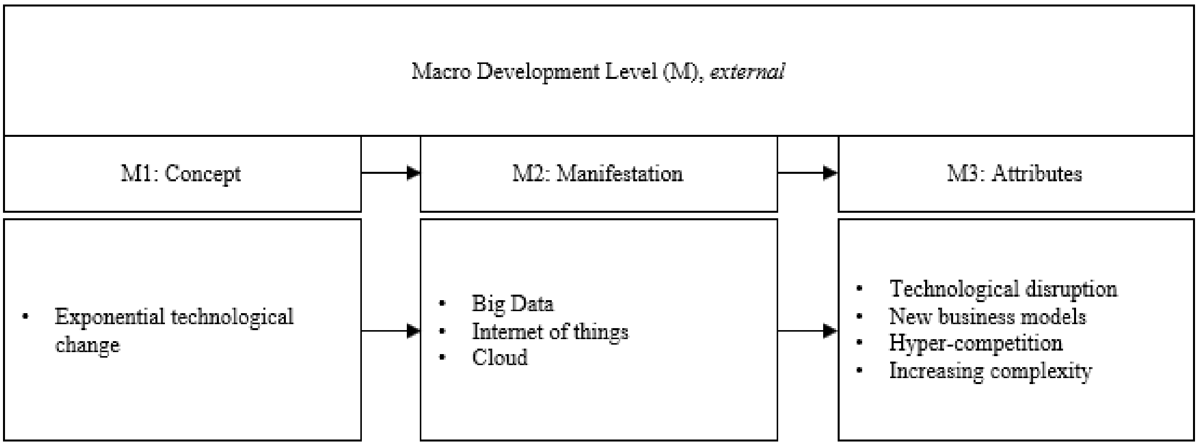



*Figure 6: IKTF macro development level*

Figure 6 shows, that the core concept of (M) is defined as the already described core concept exponential technological change, which results in the manifestations as described in Table 1.

*Table 1: IKTF macro level manifestations*

| **Manifestation (M)** | **Description** |
|---|---|
| M.2 Big Data | The increased usage of networked machines and sensors generates high-volume data. High-tech technology, like advanced machine learning, is necessary that can analyze and leverage large data sets including real-time data that are difficult to analyze by traditional methods. (Lee & Bagheri, 2015, Gaham et al., 2013) |
| M.2 Internet of Things (IoT) | The IoT enables the communication between physical and Internet-enabled devices through connecting physical objects through the virtual realm. (Mittal et al., 2017) |
| M.2 Cloud | Cloud-based IT-platform serves as a technical backbone for the connection and communication of manifold elements of Industry 4.0. and IoT as they, for example, allow flexible and cost-efficient data storage upscaling. (Rojko, 2018) |

These manifestations can now be attributed with the following properties as shown in Table 2.

*Table 2: IKTF macro level attributes*

| **Attributes (M)** | **Description** |
|---|---|
| M.3 Technological disruption | The combination of technologies like IoT, cloud and Big Data in the Industry 4.0 is disruptive and leads to significant paradigm shifts in manufacturing. CPS for example derive from important technical advances on the internet, embedded systems, computer science and artificial intelligence. (Morrar et al., 2017, Roblek, et al., 2016, Bongomin et al., 2020) |
| M.3 New business models | Industry 4.0 and its embedded technology diffusion progress is expected to grow exponentially in terms of technical change and socioeconomic impact and allow for new types of business models, for example platform business. Benefiting of such a transformation requires a holistic approach of value creation that integrates innovative and sustainable business and technology |

| | |
|---|---|
| | solutions which modify or replace existing business models. (Morrar et al., 2017, Roblek et al., 2016, Thoben et al., 2016) |
| M.3 Hyper-competition | Industrial production is driven by a hyper-competitive rivalry for market shares between formerly separated industries generated caused by a more global, digital, and interconnected market environment. (Turgay & Emeagwali, 2012) |
| M.3 Increasing complexity | Cyber-physical system architectures are characterized by unprecedented scale, information flow and interconnectedness and are thus highly complex. Managing this complexity is a challenging task, as traditional analysis tools are unable to cope with the full complexity of CPS or adequately predict system behavior. One barrier to progress is the lack of appropriate science and technology to conceptualize and design the deep interdependencies among engineered systems of the Industry 4.0 concept and the changes manifesting in the company external environment. (Rojko, 2017, Pilloni, 2018, Thoben et al., 2016) |

After describing the macro-level manifestations and attributes, the framework level can now be defined in detail.

### 3.2.2 Framework level

The Framework Level (F) represents the meso level that lies between the macro and micro level of the framework, it represents the first, conceptual company internal reaction to (M). (F) shall now be defined as the following.

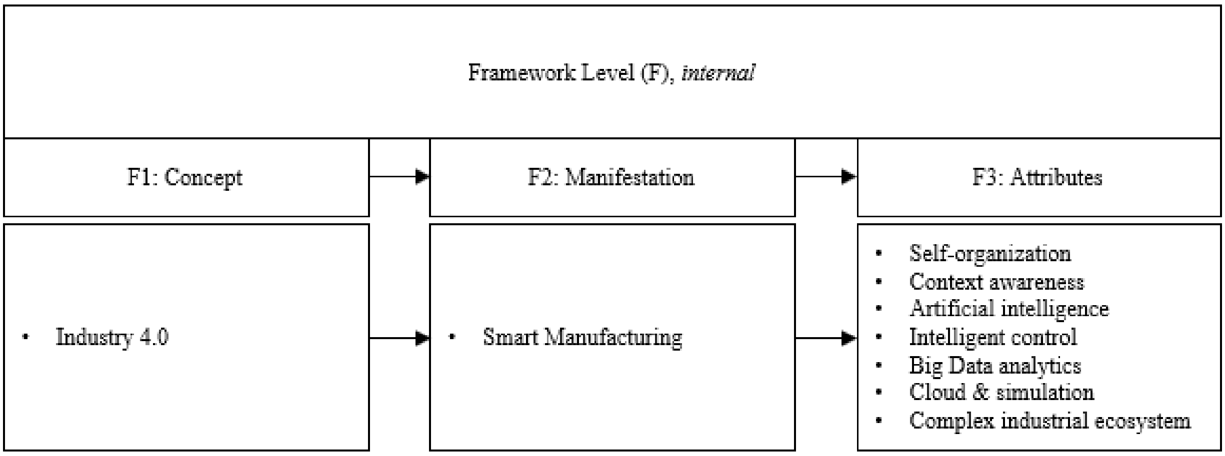



*Figure 7: IKTF framework level*

Figure 7 shows, that the concept of (F) is defined by the company internal concept Industry 4.0, which results in the already described manifestation smart factory and the attributes described in Table 3.

*Table 3: IKTF framework level attributes*

| **Attributes (F)** | **Description** |
|---|---|
| F.3 Self-organization | Manufacturing processes will be interconnected across corporate boundaries via CPS. These changes in supply and manufacturing chains require greater decentralization from existing traditional manufacturing systems. This results in a decomposition of the classic, centralized production hierarchy and a paradigm shift toward decentralized self-organization. (Lee & Bagheri, 2015, Pilloni, 2018, Roblek et al., 2016) |
| F.3 Context awareness | Context awareness is an important intelligent characteristic of a smart factory and its underlying CPS, and it is a combination of the following attributes: Awareness of identity, location, status, time. (Horvarth & Gerritsen, 2012, Bongomin et al., 2020)) |

| | |
|---|---|
| F.3 Intelligent control, artificial intelligence | With the help of intelligent technology and context awareness, a CPS is expected to be able to change its actions based on its own experience and is thus self-learning and capable of evolutionary self-adapting to external changes. If it possesses intelligent control technology, it can make use of, for example, artificial intelligence techniques, like machine learning, to control its mechanisms via decision algorithms and is able to perform more reliable and accurate in a less stable environment. (Thoben et al., 2016, Mittal et al., 2019) |
| F.3 Big Data analytics | The collection and comprehensive evaluation of data from many different sources like production equipment and systems as well as enterprise and customer-management systems will become standard to support real-time decision making. (Pilloni, 2018, Morrar et al., 2017) |
| F.3 Cloud & simulation | With Industry 4.0, organization needs increased data sharing across the sites and companies, achieving superior reaction times in milliseconds or even faster. This leads to the idea of having the connections of different devices to the same cloud to share information to one another. This can be extended to set of machines from a shop floor as well as the entire manufacturing system. Simulations will be used more extensively in plant operations to leverage real-time data to mirror the physical world in a virtual model via double representation. This includes machines, products, and humans, reducing machine setup times and increasing quality. Decision making quality can also be improved with the help of simulations, as possible system trajectories can be featured into the decision-making process. (Rojko, 2017, Pilloni, 2018, Xu & Ling, 2018, Bongomin et al., 2020) |
| F.3 Complex industrial ecosystem | Designing Industry 4.0 systems involves high complexity, which mainly originates from the high dimensionality and the internal complexity of components. As, for example, the IoT scales to |

| | |
|---|---|
| | billions of connected devices – with the capacity to sense, control, and otherwise interact with the human and the physical world – the requirements for dependability, security, safety, and privacy grow significantly and must be managed accurately. (Savastano, et al., 2019, Bongomin et al., 2020) |

After describing the framework-level manifestations and attributes, the integration level can now be defined in detail.

### 3.2.3 Integration level

The Integration Level (I) represents micro level and the company internal reaction to (F). (I) shall now be defined as the following.

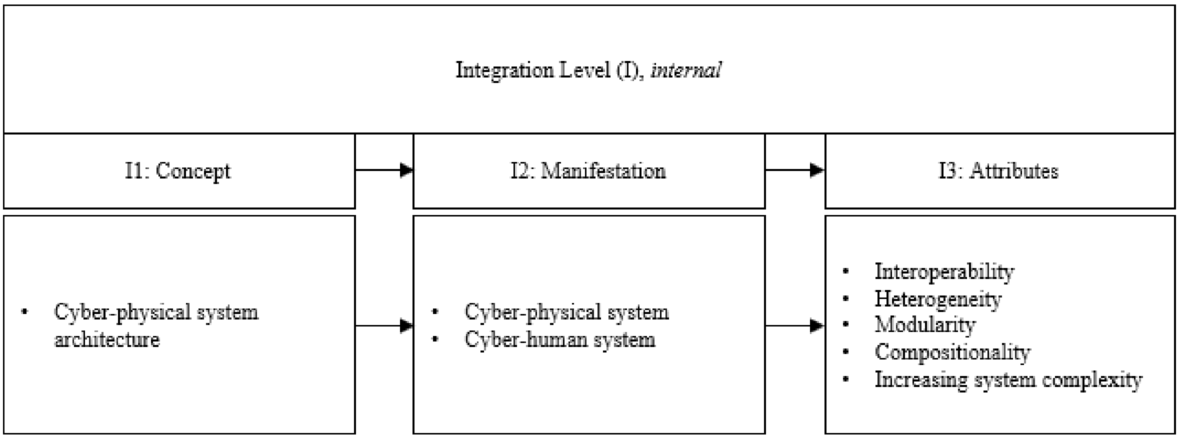



*Figure 8: IKTF integration level*

Figure 8 shows, that the concept of (I) is defined by the already described company internal core concept cyber-physical system architecture, which results in the manifestations cyber-physical system and cyber-human system and the attributes shown in Table 4.

*Table 4: IKTF integration level attributes*

| **Attributes (I)** | **Description** |
|---|---|
| I.3 Interoperability | Interoperability is the characteristic due to which, system units are able to exchange and share information with each other. With the help of networkability, systems can collaborate in different process-related aspects, and for this collaboration, they have to allow each other to share and exchange information. Similarly, distributed |

| | |
|---|---|
| | systems allow the information and data of one system to be accessed by other systems in the network. (Nagorny et al., 2017, Gaham et al., 2013) |
| I.3 Heterogeneity | Heterogeneity considers the diversity and dissimilarities in the units and components. (Thoben et al., 2016, Gaham et al., 2013) |
| I.3 Modularity | Modularity is the property of a system by which a unit can be decomposed into components that can be recombined to form different configurations. (Mittal et al., 2019, Gaham et al., 2013) |
| I.3 Compositionality | Compositionality is the property that deals with the understanding of the whole system based on the definition of its components and the combination of the constituents. (Mittal et al., 2019, Gaham, et al., 2013) |
| I.3 Increasing complexity | CPS emerge through networking and integration of embedded systems, application systems, and infrastructure, enabled by human machine interaction. In comparison to conventional systems used for production such a system is expected to be increasingly more complex. (Thoben et al., 2016, Camarinha-Matos et al., 2017) |

After presenting all levels of the IKTF in detail, it is now possible to present the complete IKTF framework.

## 3.3 IKTF: complete framework

The complete IKTF framework results and is displayed in Figure 9.

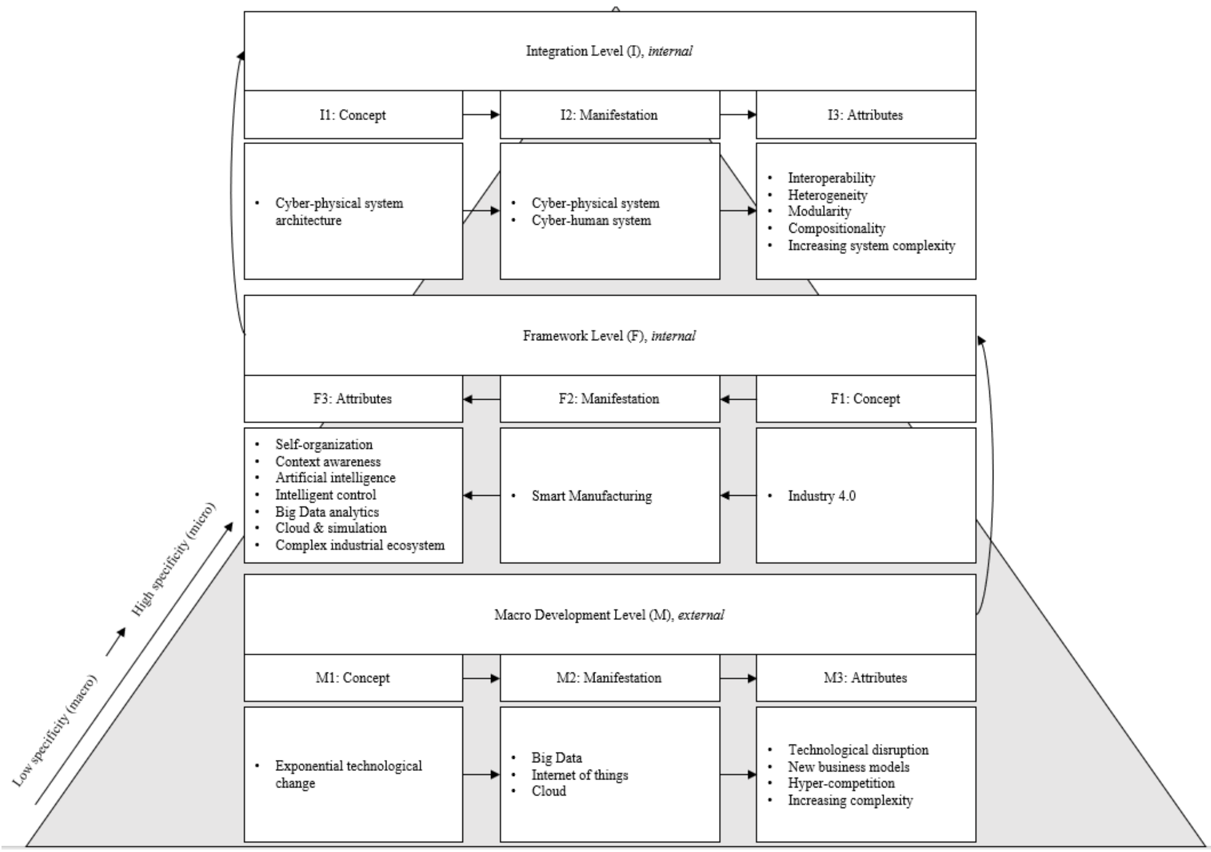



*Figure 9: IKTF complete framework*

The IKTF shows, that decision makers must acquire sufficient knowledge in the macro-level, with low context specificity (M) about the concept, manifestations and attributes of exponential technological change and its disruptive effects on the financial, political, and socio-economic external environment of the company.

This can be achieved through understanding analysing the manifestations of Big Data, Internet of Things and Cloud and their attributes of technological disruption, new business models, hyper-competition and increasing complexity in the individual corporate context.

A conceptual response through the utilization of company assets in the internal framework level (F) can then be formulated as a reaction by analysing the applicability of the concept of Industry 4.0 with its manifestation smart factory and the attributes of self-organization, context awareness, intelligent control, artificial intelligence, Big Data analytics, cloud & simulation and the complexity of industrial ecosystems under the resource constraints and macro influence factors of the individual company.

If this is achieved an integration approach can be formulated by analysing the applicability of cyber-physical system architectures, their manifestations cyber-physical systems and cyber-human systems with the attributes of interoperability, heterogeneity, modularity, compositionality and increasing complexity under the identified constraints on the framework level and macro level.

This makes visible that a successful integration of Industry 4.0 is an extensive, difficult to achieve task which requires extensive knowledge, reflection, and insights on all levels of specificity.

According to the IKTF no level of the framework can be skipped or only partially understood. Only a comprehensive understanding of the framework levels and the successful application on the individual corporate context allow a successful integration of Industry 4.0.

This highlights the importance of informed, strategic and analytical decision making on all corporate areas in the context of Industry 4.0 integration.

## 3.4 Increased system complexity as a conclusion to the IKTF

Next to the mentioned aspects, it is also shown by the IKTF that complexity plays a major role on the micro, meso and macro level of the framework.

Complexity in the context of the IKTF has thus to be regarded as one of the most essential attributes of Industry 4.0. The following Table 5 now provides a short overview of the resulting complexity attributes in the IKTF.

*Table 5: Complexity as a conclusion to IKTF*

| **Level** | **Complexity** | **Description** |
|---|---|---|
| Macro (external) | Increasing complexity | Exponential technological change leads to the emergence of new and more complex, interconnected technological environment. |
| Framework (internal) | Complex industrial ecosystem | The enabling of the smart manufacturing approach leads to possibility to implement and utilize the potency of highly complex industrial ecosystems. |
| Integration (internal) | Increasing system complexity | Highly complex industrial ecosystems are attributed with a complex CPS architecture. |

The following Figure 10 now summarizes the meaning of complexity for the firm in an Industry 4.0 context according to the IKTF.

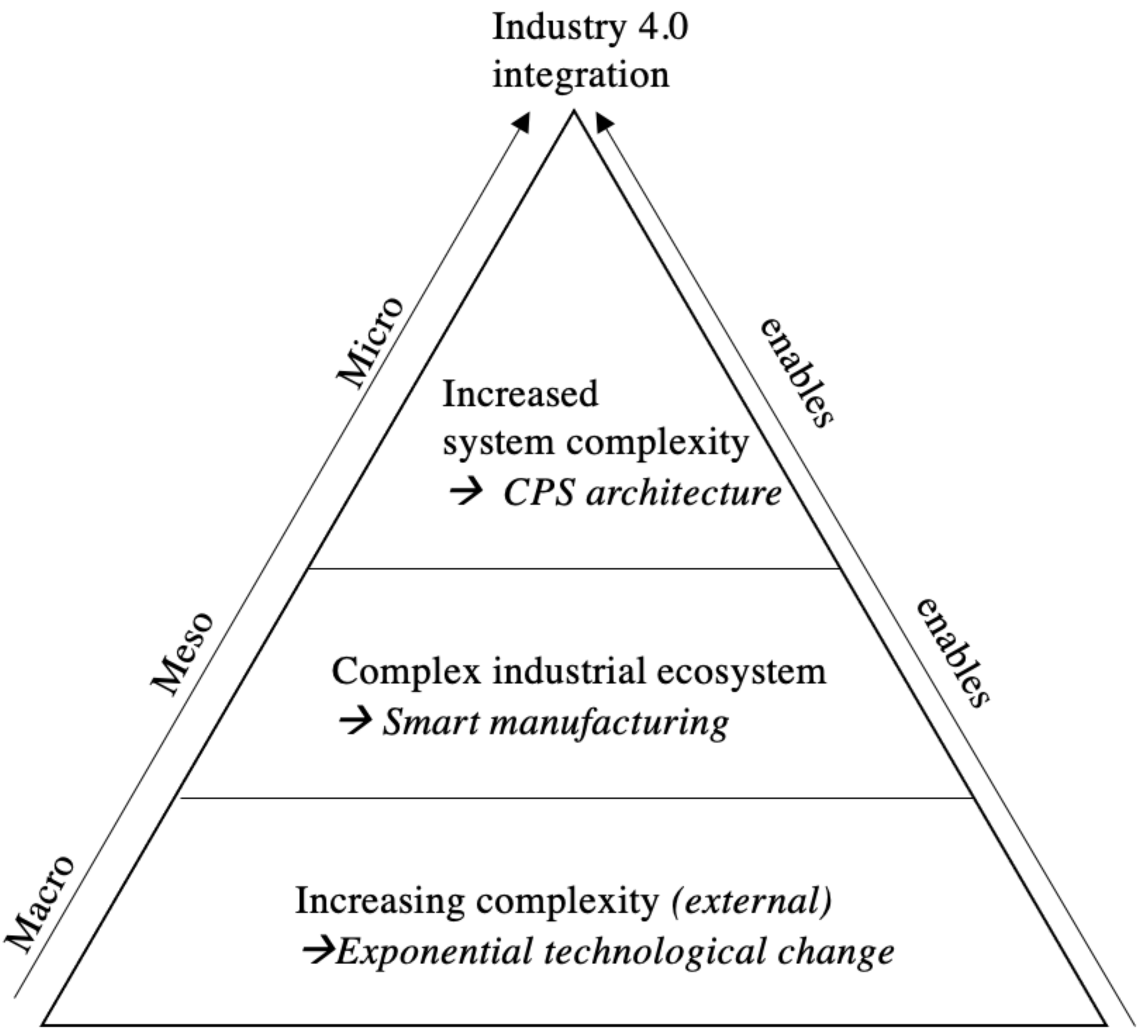



*Figure 10: Components of Industry 4.0 integration*

Based on these insights it can now be stated that the IKTF example shows that the successful integration of Industry 4.0 is dependent from many layers of understanding which are sequentially connected on the micro-meso-macro levels of analysis.

It is implicated that the integration of Industry 4.0 is accompanied by a large variety of research and development issues, for example the management of system complexity and the development of universally applicable reference models and foundational definitions of fundamental concepts for Industry 4.0.

To summarize the implications introduced by the IKTF, the concept of Industry 4.0, represents, in theory, a transformative, evolutionary advancement from traditional embedded systems in manufacturing to highly complex smart industrial production systems defined by autonomous, interconnected CPS.

A successful transformation is expected to allow the paradigm change from a standardized mass-production system to a customizable, flexible, cost-efficient and demand responsive production that can efficiently fulfil the requirements of global, volatile, and hyper-competitive market environments.

Even though the vision and the concept of Industry 4.0. are already well-described on a theoretical level, several unsolved challenges, like the challenge of complexity, on the technological, integrative/ managerial, and general level of understanding remain to be better understood and captivated.

These challenges effectively inhibit a successful integration of the concept of Industry 4.0 in applied manufacturing systems.

It can therefore be concluded that the concept of Industry 4.0 while still not fully developed, is ambiguously connected to a variety of other challenging meta-concepts or sub-concepts, like the increasingly difficult to conceptualize and manage complexity dynamics of the CPS components of current and future industrial manufacturing systems.

Thus, the application of complexity on the manufacturing process in general and therefore the utilization of different CPS combinations across the value chain in the context of Industry 4.0 enables great capabilities for innovation, within and across existing and future fields of application.

In contrast to the potential of CPS it is well understood that already current systems are stretching the limits in terms of development of cost-efficient and trustworthy systems. It can be stated that today´s CPS system design is unable to support the level of complexity, scalability, security, safety, interoperability, and flexible design and operation that will be required to meet future needs. (Törngren & Sellgren, 2018)

This statement is supported by Cotrino et al.  (2020) who identify in their research a significant strategic gap regarding the development of strategies to deploy Industry 4.0 technologies, especially in the context of small-medium enterprises.

This leads up to the conclusion that future CPS can be expected to be of unprecedented complexity and obtaining an understanding of the meaning of complexity in the context of CPS is an important asset to assure CPS functionality in the many CPS application fields that are vital for society, as well as business, and rely on optimal and safe CPS performance.

One barrier here can be defined as the circumstance that an assessment of complexity cannot, and thus is not, typically made in industry at the design phase as managers and other key stakeholders require practical and efficient methods for measurement, which are often not available to them. (Törngren & Sellgren, 2018)

In the terms of strategic management of complexity there is also a strong indication in the IKTF that the value of complexity management strategies increases as the complexity of the managed manufacturing system increases.

The presented line of arguments makes visible that it is now imperative for industry decision-makers to obtain methods and tools of strategic planning addressing the management of complexity in industrial systems, like CPS system architectures, which is line with the research objectives and the aim of this thesis.

Consequently, the topic of complexity is introduced in the section to follow as a starting point to develop a comprehensive understanding of the topic of strategic complexity management for industrial systems.

# 4 Complexity

This chapter now introduces the topic of complexity in the context of industrial systems. This is achieved to providing a brief overview over the terms complexity science, the process of defining complexity, scientific models based on complexity science and the concept of emergence. Consequently, the next section now discusses the topic of complexity science.

## 4.1 Complexity science

The science of complexity is often said to be an integral part of a new unifying theory of science that breaks with the traditional or “classical” Newtonian mechanistic scientific method of analysing, isolating, and gathering complete information about a phenomenon in the form of a model of the object of research. (Wolfram, 2002)

In this light Homer-Dixon (2011) postulates the thought that a shift is necessary away from seeing the world as composed of simple machine to seeing it composed as of complex systems.

Heylighen et al. (2006) state in this context that the traditional scientific method, which is based on analysis, isolation, and the gathering of complete information about a phenomenon, is incapable to deal with such complex interdependencies.

This shows that the idea of the world as complex systems may allow to improve the understanding of complex and hard to predict systems that spread over various scientific disciplines, like the human brain in the field of biology, industrial systems engineering and management or the world economy in the field of the social sciences, indicating a strong interdisciplinary nature of thinking. (Ladyman et al., 2013, Mesjasz, 2010, Heylighen et al., 2006, Frenken, 2006, Phelan, 2001, Homer-Dixon, 2011)

The idea of complex systems and their underlying definitions of complexity are thus becoming more important in both natural and social sciences.

## 4.2 Defining complexity

Even though the importance of understanding complex systems and their influences on various disciplines of science is undenied by many scientists there is no definitive consensus on a concise definition of a complex system. Consequently, various and differing definitions of the terms “complexity” result and coexist and the conceptual framework of complexity is still lacking in applicability and precision and often either loses itself in mathematical intricacies or philosophical vagueness. (Ladyman et al., 2013, Heylighen et al., 2006, Edmonds, 1995)

In this context Edmonds (1995) already introduces the thought that many complex systems are in practice intractable which allows the assumption of all conducted theories to be inapplicable in practice and leads to the thought of the debate about complexity being a purely philosophical and non-practical issue.

Therefore, various non-conclusive attempts exist to define the role of complexity in science and relevant research attempts often focus on collecting, summarizing, and discussing the various attempts established over time, as shown by the work of Ladyman et al. (2013), Mesjasz (2010) and Heylighen (2007).

Due to the multitude of definitions the question arises if there is a single natural phenomenon of complexity or at least a strong common denominator of the type of a second law of thermodynamics that can be subjected to a specific scientific approach, coined as "a new kind of science" by Wolfram (2002), or if there are several types of complexity coexisting that may not share a common nature.

Voices critical of the idea of a common denominator like Mesjasz (2010) argue that the attempts of scientist to define complexity results in a" complexity of complexities", therefore relating to the impossibility to define an overarching universal theory of complexity.

This circumstance additionally relates to the thoughts of Bechtel & Richardson (2000) and Ladyman et al. (2013), who articulate that the analysis of complex systems requires the consideration of multiple perspectives.

They conclude that theoretical insights of already established analytical frameworks in the field of complexity science should serve as a starting point for the development of future explorations and as a source of creativity and not as the determining path for possible explorative directions.

This notion strongly relates to the idea that it is necessary to develop an "intuition" for what complexity could be through studying complex systems. (Homer-Dixon, 2011)

Based on these thoughts, the next section now introduces a general definition of complexity for the purpose of this thesis.

### 4.2.1 A general definition of complexity

In general, complexity shall now be defined according to Sherman & Schultz (1998) as a preliminary baseline definition at this point in the thesis before discussing industrial systems as a complex system:

*"Complexity refers to the condition of the universe which is integrated and yet too rich and varied for us to understand in simple common mechanistic or linear ways. We can understand many parts of the universe in these ways, but the larger and more intricately related phenomena can only be understood by principles and patterns – not in detail. Complexity deals with the nature of emergence, innovation, learning and adaptation."*

Consequently, complexity shall be regarded for this thesis as a fundamental property of every dynamical system, which, in principle, can be assumed to be understood, measured, and managed.

This allows to conclude that, if complexity can be managed by human activity, it becomes a strategic asset of the system for the decision-maker managing the system as a logical consequence.

Therefore, this thesis does refute the stance that complexity science and related methods, especially in the managerial sphere, are non-applicable in theory and thus without value in practice.

Consequently, this thesis thus assumes the stance that complexity is to be regarded as a strategic asset of any industrial system that can generally be managed and leveraged for a given definition of managerial success by the decision-maker.

Reversely and as a logical consequence of this proposition, complexity must be become a potential threat for any system and managerial success if it is not adequately managed by the decision-maker.

Based on this definition and to provide a wider context, the next section now illustrates and discusses the topic of scientific models and the "shift away from" classical Newtonian mechanics and analysis through the assumptions of complexity science.

## 4.3 Scientific models based on the assumptions of complexity science

The described shift away from "classical" science is expressed by Downey (2012) as a gradual shift in the criteria scientific models are judged by.

These assumptions lead, according do Downey (2012) and Knyazeva (2020), to the following evolutionary shift in the establishment of scientific models along two central axes of analysis:

- **Equation-based, positivistic and reductionistic**: evolves to dynamic, holistic, potentially simulation-based.
- **Analysis through mathematical deduction:** evolves to pragmatic or computation based.

Both axes have a significant impact on how models based on complexity science generate knowledge, as they now serve in a more explanatory instrumentalist function instead of the "classical" more realist positivistic predictive function of traditional scientific models. (Knyazeva, 2020) Such models are already well represented by Schelling´s (1971) dynamic models of segregation (Schelling, 1971, Hatna & Benenson, 2011) or by cellular automata models (Wolfram, 2002) and have had a significant impact on their respective fields of research in the last decades. What these models have in common is that they are built on the twin-theme assumption that simple behaviours can produce complexity, as for example illustrated by Wolfram´s (2002) cellular automata or Schelling´s model of segregation, while complex or even chaotic behaviours paradoxically produce simplicity, as showcased by the research of Steward & Cohen (2000) It can now be stated that complexity science expands on the reductionistic, equation-based Newtonian framework by striving to not only understanding the parts that contribute to the whole but by understanding the nature and dynamics of how each part interact with all the other parts and emerges into a new meta-entity with its own behaviour. It is thus aiming to achieve a more comprehensive and complete understanding of the whole because of the holistic nature of the scientific inquiry. Under these assumptions, individual causal research concerning individual components in complex systems is assumed to be near futile and comprehensive, holistic approaches are required to account for the unpredictability found in complex systems. (Westhorp, 2012) In this light, new theoretical models that reflect "real-life complexity" of researched systems are being called for by researchers. (Haslberger, 2005, Turner & Baker, 2019, Knyazeva, 2020)

The next section now briefly illustrates how traditional complexity models, like the Schelling model, are structured and function in principle to reflect the introduced notions.

### 4.3.1 How complexity models work

In the Schelling model, agents occupy cells of rectangular space. A cell can be occupied by a single agent only. Agents belong to one of two groups and can relocate according to the fraction of friends (i.e., agents of their own group) within a neighbourhood around their location.

Figure 11 now illustrates the original Schelling model.

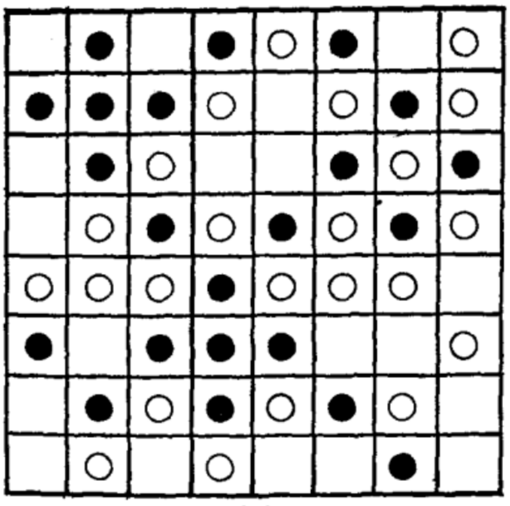


*Figure 11: Schelling model basic structure (Hatna & Benenson, 2021)*

Figure 12 now illustrates the Schelling model when used for computer simulation and how it manifests segregation effects in a population represented by black and white squares.

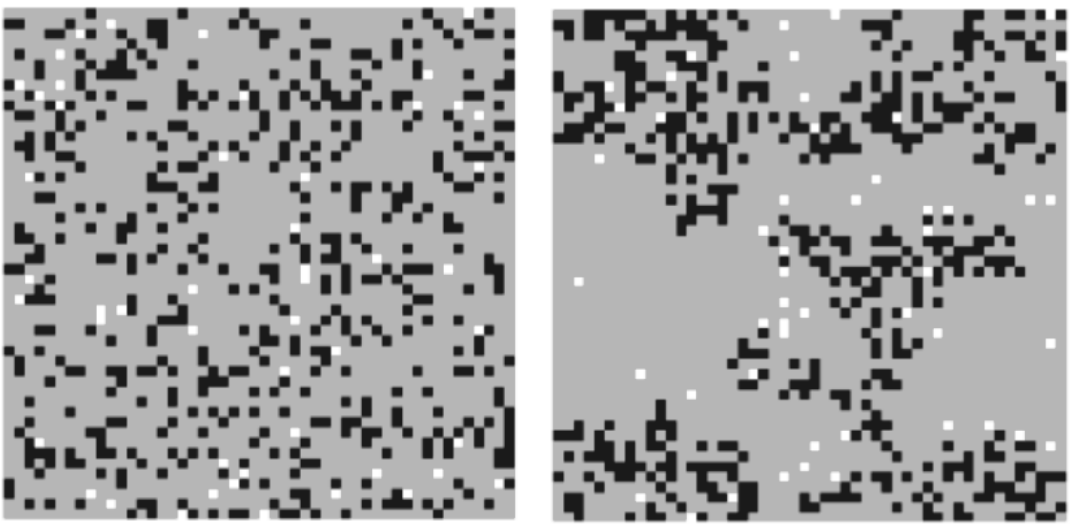


*Figure 12: Segregation in the Schelling model (Hatna & Benenson, 2021)*

Figure 13 now illustrates the Schelling model when used for simulation of segregation behaviour reflected by ethnic residential patterns over time in real world cities, again represented by black and white squares.

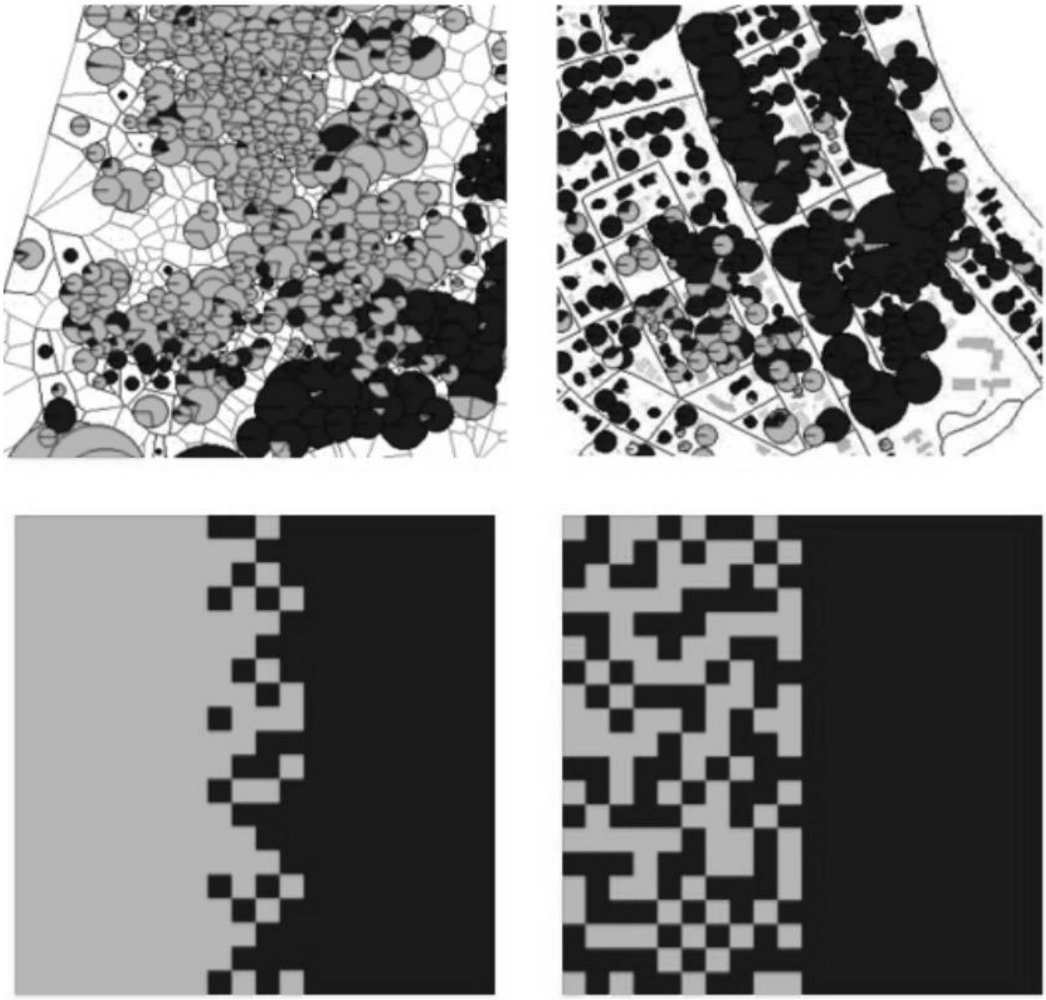


*Figure 13: Real world segregation in the Schelling model (Hatna & Benenson, 2021)*

As shown in Figure 13, the Schelling model therefore allows to illustrate how individual incentives and individual perceptions of difference can lead collectively to complex urban segregation phenomena, based on the application of simple rules. (Hatna & Benenson, 2011)

Preiser & Woermann (2018) add to these notions, that the necessary reductions applied to the system under study through modelling lead to the impossibility of objective knowledge of complex systems as these necessary reductions are subjectively defined for the instrumental purpose of the model.

These assumptions manifest in different concrete modelling approaches for complex systems like discrete-time models, continuous-time models, cellular automata, continuous field models, agent-based models, network models or heuristic approaches. (Sayama, 2015, Wolfram, 2002, Knyazeva, 2020)

After exemplifying how complexity models are defined and function, the next section covers another central topic to complexity by defining the term *emergence*.

## 4.4 Emergence

Emergence is central topic in complexity, often as philosophical as it is of practical importance. As the topic of emergence can be discussed exhaustively in several areas, strong individual challenges remain to be answered. In response to these circumstances, a brief discussion of emergence as a property of complex systems shall be introduced in this section.

Emergence is a property of a complex system resulting directly from the system's evolution and occurs independently. Emergence means "to dive out" or to come out of the depths.

In the context of complex systems, emergence relates to the apparition of new system behaviour due to the collective behaviour of the parts, as opposed to the individual behaviour of each part, and the system's response to its environment. Emergence is an important characteristic of complex systems theory as it allows the identification of new opportunities. (McCarthy et al., 2000, Mainzer, 2004, Mittal et al., 2018, Fromm, 2004)

This results in the general concept of "more is different".

For example, emergence occurs in natural systems when water as a complex system of molecules changes spontaneously from a liquid to a frozen state at a critical temperature of zero Celsius.

Another illustrative example would be the behaviour of a flock of birds, which is generally unexplainable by simply analysing a single bird´s behaviour.

Anderson (1972) already summarized the idea of emergence by stating that a change of system scale often causes a qualitative change in system behaviour. He provides the following examples:

*"One water molecule is not fluid,*

*One gold atom is not metallic,*

*One neuron is not conscious,*

*One amino acid is not alive,*

*One sound is not eloquent."*

To further define the concept of emergence in more detail it is possible to introduce the relevant main properties of emergence to narrow down on how emergence can work.

Based on the work of Stepney et al. (2006) the following main properties of emergence in a system can now be coherently introduced:

- **Far from equilibrium:** The system is an open far from equilibrium dissipative process, that is, with a constant flow of matter, energy, or information (entropy) through it. It exists in a context, or environment, which provides the material from which it organises its relatively stable pattern of existence. The properties of the system depend not purely on its own organisation, but also on this context, and the boundary (or initial) conditions.
- **Levels:** The system has different levels, exhibiting different length- and timescales. The dynamics of the lower levels exhibits attractors. These attractors are identified with higher level emergent properties: extended low-level processes become high level atomic states, with their own dynamics.
- **Languages:** The system has a low-level language L, used to describe the implementation, cast in terms of the local components and their local interactions, and a high-level language H, used to describe the resulting system. H employs concepts distinct from those of L, and, is cast in terms of more global concepts (concepts encompassing larger spatial or temporal scales).

Based on Mittal et al. (2018) emergence can now be fundamentally defined as

*Emergent behaviour (System) = components + interactions + higher order effects*

Based on this definition the next section now introduces and briefly describes different types of emergence.

### 4.4.1 Types of emergence

Mittal et al. (2018) identify four types of emergence. These can be defined as the following:

- **Simple emergence:** Refers to simple systems, cause-and-effect relations are perceivable, repeatable, and predictable. The emergent property is readily predicted by simplified models of the system.
- **Weak emergence:** Refers to complicated systems, the cause-and-effect chains can be understood by reductionism and detailed analysis. Emergent behaviour in this system category is reproducible and consistently predictable. The emergent property is reproducible and consistently predicted with simulation.
- **Strong emergence:** Refers to complex systems, the cause-and-effect relations are only coherent in retrospect and usually do not repeat. Although the behaviour is consistent and explainable within the system, it is not reproducible. The emergent property that is consistent with known properties but not reproducible in the simulation. It is unpredictable and inconsistent in simulation.
- **Spooky emergence:** Refers to complex systems, spooky emergence is not predictable due to the absence of a system model that can explain the observation. The emergent property is inconsistent with the known properties of the system.

This now allows to conclude that complex systems are expected to be mainly impacted by strong or spooky emergence. (Mittal et al., 2018)

This notion is consistent with Ashby (1991) and Steward & Cohen (2000) who state that the main source of emergent behaviour is lack of knowledge about the system, implicating a strong human factor of how different human minds perceive and understand the complexity of a system.

In conclusion, it can be stated that the embracement of the complexity perspective involves the shift of emphasis from *how something works* to *how something behaves*. (Wade & Heydari, 2014)

To provide further information on the practical relevancy of complexity the next chapter now introduces the topic of complexity in business by presenting and discussing the concept of VUCA.

## 4.5 Defining complexity in the business environment

According to Turner & Baker (2019) and Knyazeva (2020) and as shown by the IKTF in Chapter 3, the implementation of new technological innovations causes the intensification and manifestation of complexity in business environments.

In this line it is stated that organizations need to manage this growing complexity through the adoption and diffusion of complexity science in a managerial theory, a perspective of analysis, in which organizations are viewed as emergent, complex systems that cannot be observed using traditional analytical linear methodologies. (Turner & Baker, 2019, Knyazeva, 2020)

According to Bennet & Lemoine (2014), Potsangbam (2017), Krawczynksa-Zaucha (2019), Milar et al. (2018) and Liang & Gou (2021) decision-makers face in this context surging increases in volatility, uncertainty and overall business complexity leading up to more emergent, unstable, and therefore unpredictable business environments, which are named VUCA environments.

Based on Mohanta et al. (2020) it is now possible to describe the dimensions of VUCA in more detail.

- **Volatility:** Indicates extreme and rapid fluctuations in business environment. The pace, the volume and the magnitude of change can define as the degree of turbulence it creates, in the business or industrial environments.
- **Uncertainty:** The lack of knowledge about the situations causes uncertainty in any field which results an unpredictable future and affects the long-term grown of that organization.
- **Complexity:** With the rapid industrialization, complexity arises due to the interconnected parts, networks and procedures within the organization in combination with the external business environment. Both might even be unidentifiable and contradicting with each other and lead to complexity in decision-making.
- **Ambiguity:** If the problem statement lacks clarity, confidence in probability assessments and the diversity of potential results in which the outcome cannot be clearly described then it is termed as ambiguity in business environment.

After defining VUCA, the next section now further expands on the importance of VUCA for management.

### 4.5.1 VUCA and the increasing importance of complexity science for management

deMattos et al. (2012) describe three trends that are contributing to the increasing importance of complexity science for management:

- **Change:** Changes are taking place for both organizations and governments in part due to globalization, intensive local and global competition, process re-engineering, workforce diversity, quality improvement, and continual exponential technological innovation.
- **Information revolution:** The productivity of information processes is increasing, and costs are declining (e.g., information retrieval, processing, and storage).
- **Companies fail:** Organizations are dissolving at alarming rates.

The components of the VUCA-world thus represent the main challenges for doing sustainable business and designing strategy in the modern business world. It also gets visible that they strongly relate to the challenges generated by Industry 4.0.

They are consequently adopted by business leaders and decision-makers in the manufacturing industries to describe and address the rapid changes of the business environment and to capture and benefit of overcoming challenges and newly arising opportunity.

VUCA is furthermore in stark contrast to classical management theory, since Taylor's scientific management theory emphasizes that optimal scientific management should be based on a Newtonian conception of clearly defined laws, regulations, and principles which connect cause and effect in a mechanistical manner. (Dean, 1997)

This is reflected in the work of Aritua et al. (2009) who have challenged the discipline of management to draw on research from complex, dynamical systems and from complexity theory to gain new insights into developing new techniques and methodologies.

In the context of industrial systems, the implications of the VUCA-world for business and strategy can be applied to the already described rise of CPS in Industry 4.0. (Mohanta et al., 2020)

Based on the introduced statements, Figure 14 now introduces a slightly modified, complexity centred, definition of VUCA for this thesis.

### 4.5.2 A complexity centred definition of VUCA

Figure 14 shows that, VUCA shall still be defined by volatility, uncertainty and ambiguity and complexity as the core challenges to decision-making in modern and future business environments.

In the provided figure the term complexity is now centred at the middle of all other terms since the complexity shall be regarded as the central aspect and challenge to be overcome to achieve more efficient and effective decision-making.

Uncertainty, ambiguity, and volatility are thus regarded as derivates or symptoms of complexity for this thesis.

It can also now be argued that uncertainty, ambiguity, or volatility alone may not be necessarily sufficient to make a situation complex in way that it causes strong or spooky emergence.

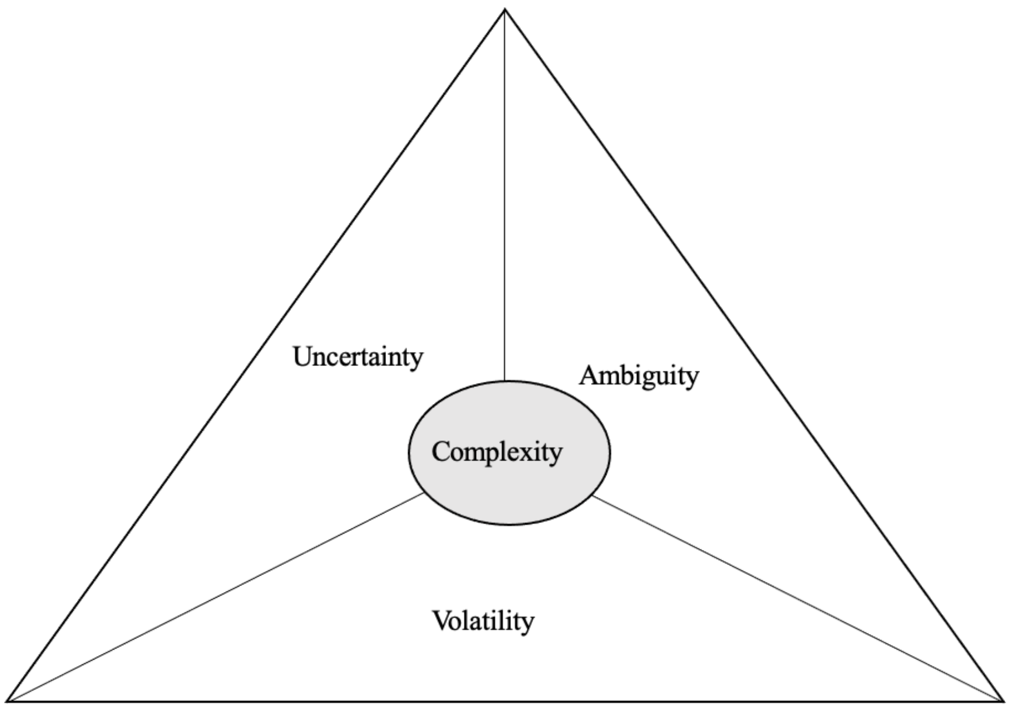



*Figure 14: Complexity centered VUCA definition*

Nevertheless, it can be established that individual VUCA aspects on their own can already lead to overwhelming challenges, a combination of VUCA aspects or the presence of all aspects combined can lead to complex business problems that are nearly unsolvable for decision-makers by traditional means of analysis. (Krawczynksa-Zaucha, 2019, Milar et al. 2018)

The next section now defines the requirements for effective strategy in a VUCA environment.

### 4.5.3 Requirements for effective strategy in a VUCA environment

According to Busulwa et al. (2018) and Knyazewa (2020) decision-makers must implement the following key aspects to enable strategy in a VUCA environment.

- **Clear understanding:** Decision-makers need to get a clear understanding of the different dimensions of complexity and develop the ability to diagnose the dimensions of complexity that are at play.
- **Right type of strategy:** Decision-makers must ensure that their organisations pursue the right types of strategies for their individual environment.
- **Effective strategy execution:** Decision-makers must ensure that their organisations use the most effective strategy execution processes to realise those types of strategies.

These aspects underline the importance of developing VUCA strategies for decision-makers in complex environments that synergize different complexity dimensions.

It can be concluded that VUCA brings challenges to many areas of management, including design innovation, organizational structure, strategic planning, ecosystem management, manufacturing, talent management or strategic partnership. (Liang & Gou, 2021)

VUCA furthermore underlines the increasing importance of the application of complexity science in industrial engineered systems management to overcome the current and upcoming challenges decision-makers face. (Mohanta, 2020)

It is furthermore shown that the capability to identify complexity dimensions and to derive effective strategies based on the identified complexity dimensions again underlines the relevance of strategic complexity management. (Knyazewa, 2020)

In the light of the statements established, the next chapter now introduces the topic of complexity in industrial manufacturing systems by providing definitions for different types manufacturing complexity, complexity symptoms and assessment methods.

# 5 Defining complexity in industrial manufacturing systems

This chapter now introduces the concept of manufacturing complexity. To achieve this, an overview of the current body of literature is provided in three areas:

1. Complexity types
2. Complexity symptoms
3. Complexity assessment methods

Consequently, the next subsection describes different types of manufacturing complexity relevant for this thesis.

## 5.1 Types of manufacturing complexity

Complexity in manufacturing systems can be generally defined within two domains: static and dynamic, as shown in Figure 15. (Frizelle & Woodcock, 1995, Alkan et al., 2018)

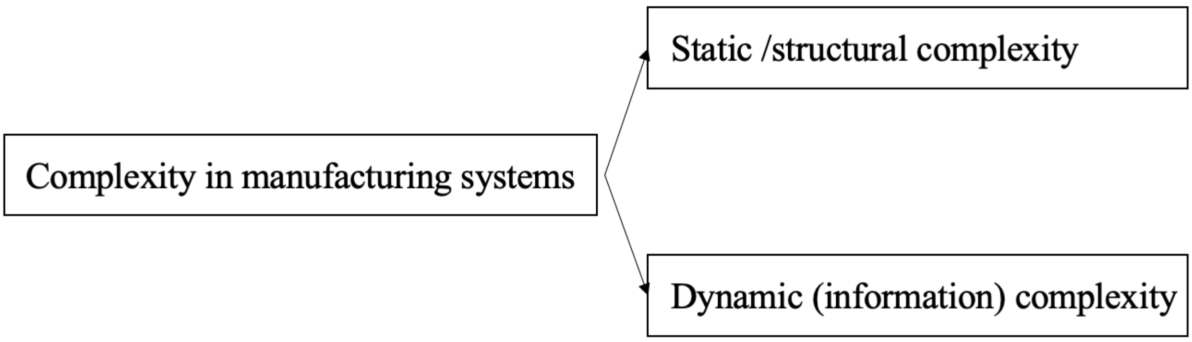



*Figure 15: Domains of complexity in industrial systems*

Based on Alkan et al. (2018), the showcased complexity types are defined in more detail. It is important to mention that the definitions focus on complexity of design not complexity of use.

- **Static / structural complexity:** Represents time independent characteristics of a manufacturing system and focuses on types of sub-systems and strength of interconnections.
- **Dynamic complexity:** Represents system's operational characteristics and involves aspects of time and randomness, dynamic complexity is often associated with a system deviating from its performance expectations due to the unpredictability.

The next section now elaborates on objective and subjective sources of complexity in manufacturing systems.

## 5.2 Objective and subjective complexity in complex manufacturing systems

Based on Törngren & Grogan (2018) dynamic and static complexity in CPS manufacturing systems can furthermore be defined as either a subjective or objective complexity source.

These definitions differentiate between the objective, technical dimension of complexity that is varying between mechanical (reducible or decomposable) and systemic (irreducible) problem types which is assumed to be perceived by an *omniscient designer*.

On the other hand, there is the subjective or social dimension of decision-making in the context of the technical dimension of a system which is highly dependent on the *non-omniscient* perceiver, namely the strategic decision-maker.

The most complex problems consequently incorporate systemic-pluralistic contexts where technical and social sources complicate decision-making due to an inability of the decision-maker to understand and link inter-dimensional cause-and-effect relations and to create a strategic vision of complexity. (Knyazeva, 2020)

This situation is also often combined with a general lack of local, causal control over the decision-making process by the decision-maker, leading up to a lack of control in the decision-making process. (Jackson & Keys, 1984, Törngren & Grogan, 2018, Knyazeva, 2020)

Based on Törngren & Grogan (2018) and Wade & Heydari (2014) objective and subjective sources of complexity are now further defined:

- **Objective:** Represents an inherent amount of work or information in a system independent of the people involved. They represent sources of effort for a hypothetical omniscient designer to achieve desired system functions with perfect knowledge. Thus, complexity is regarded as ontological.
- **Subjective:** Subjective sources of complexity consider the challenges to interpreting, understanding, and anticipating design as a human activity rather than an omniscient one. Thus, complexity is regarded as epistemological.

Based on these notions and according to Ameri et al. (2008) it is useful for design engineers to be equipped with objective, quantifiable measures of complexity aiding in rational design decision making. The measures in this regard are seen as objective in that they are dependent not on an engineer’s interpretation of information, but rather on a model generated to represent the system to be analysed. (Ameri et. al., 2008)

Contrasting this aim, in practice there are many different representations of system complexity existing to describe and analyse the complexity of a given manufacturing system, underlining the hypothetical nature of objective complexity, and illustrating the highly subjective component of system complexity analysis. (Törngren & Grogan, 2018, Schöttl & Lindemann, 2015, Wade & Heydari, 2014) This notion is supported by Suh (2001) who states that complexity can be regarded as a relative measure relating to what is the desired objective against what is known and unknown.

Figure 16 now illustrates this.

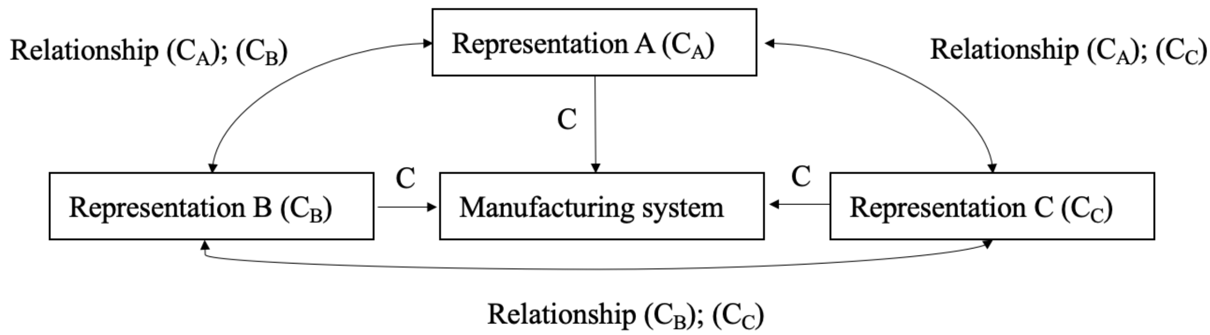



*Figure 16: Different representations of system complexity*

Figure 16 shows that different representations portray different views of manufacturing system complexity (C) in relation to the respective system and the underlying system target function. $C_A$, $C_B$, and $C_C$ now represent the complexity of the system with respect to representation A, B, and C. The question that now arises is whether these complexity measures are correlated with each other or not. If these measures are assumed to be correlated it is possible to argue that a holistic perspective might be beneficial to analysis meaning that it is imperative to study complexity of a single system from multiple perspectives and perceived complexities. (Ameri et al., 2007, Knyazeva, 2020, Schöttl & Lindemann, 2015) This stance is well summarized by Luhmann (2013) who states that if an observer is introduced one always faces the questions of who says a particular thing, and who does something, and from which system perspective the world is seen in a particular way. The introduced notion of varying and different complexity representations of a system are additionally supported in practice by Rouse (2003) and Schöttl & Lindemann (2015), who observe that the degree by which a system is perceived as complicated, or complex do vary with the level of education of the system engineer.

After introducing the different concepts of manufacturing complexity, it is now possible to discuss the symptoms of complexity in industrial manufacturing systems in the next section.

## 5.3 Symptoms of complexity in industrial manufacturing systems

The following categories of complexity symptoms in industrial manufacturing systems are described in this section:

- Symptoms observed from nonlinear behaviours
- Symptoms observed via operational uncertainties
- Symptoms observed from the physical situation
- Symptoms observed from human perceptions

Consequently, the symptoms observed from nonlinear behaviours are now described.

### 5.3.1 Symptoms observed from nonlinear behaviours

The most typical feature of complex systems is the existence of nonlinear behaviours. In the literature, several studies perceive complexity in the existence of symptoms associated with unstable dynamic phenomena whose identification often require scanning of production records over a reasonable time interval. (Alkan et al., 2018, Frizelle & Suhov, 2008)

Based on the research of Gahrbie (2013) these symptoms are described in more detail:

- **Repeating patterns:** The existence of repeating patterns observed in the long-term behaviours of production systems. In this context, long-term behaviours indicate the interaction and evolution of dynamic system parameters which are defined by geometrical structures generated through phase space reconstruction methods.
- **Sensitivity to initial conditions:** Systems exhibiting large deviations in meeting due dates or performance goals by even small changes in initial conditions or production control parameters can be considered as complex. This symptom is a result of both static and dynamic complexity resulting from the factors such as production delays, multiple-feedback loops, and external and internal disturbances.
- **Emerging dynamic behaviours:** Dynamic behaviours emerging from the coupling between the intrinsic configuration of the system and uncertainty linked with system's operations. This symptom reflects static complexity occurring due to structural alterations (e.g., adding/removing equipment).

The next section now describes symptoms observed via operational uncertainties.

### 5.3.2 Symptoms observed via operational uncertainties

An increase in complexity results in various operational problems including batch-and-queue decision-making inefficiency, lack of process synchronisation, increased lead and ramp-up times, and performance fluctuations. (Alkan et al., 2018, Frizelle & Woodcock, 1995, Frizelle & Suhov, 2008)

Based on Alkan et al. (2018) the introduced symptoms can be described as the following:

- **Increased amounts of information:** This symptom reflects the inherent effort of the process for producing the required quantity and kind of products in a certain time interval and it arises due to the various factors, including increased number of parts, operations and machines, increased sequence flexibility, and increased resource sharing. In this context, information content is linked to the uncertainty associated with the probability of an entity being in a predefined state.
- **Operational dynamism:** Is occurring due to several factors such as: part reject, rework, absenteeism, and resource breakdowns, etc. Accordingly, systems in which it is difficult to monitor their operational status, can be considered as complex. In this context, complexity is estimated by analysing the deviation between observed and scheduled resource states (in other words, the probability of a resource being out of schedule) which is captured through real-time process observations taken at regular intervals.
- **Uncertainty in handling increased product variety:** Uncertainty in handling increased product variety which is often linked to the risk factors associated with operator's choices of tools, fixtures, and assembly procedures. In this context, complexity is referred as the averaged vagueness in a random process of managing a number of product variants, which depends on the sum of the introduced varieties at a workstation and the conveyed varieties from all the upstream workstations.
- **Uncertainty associated to the predictability of manufacturing operations:** This symptom is a consequence of dynamic complexity occurring due to the factors such as: incompleteness of information, disturbances, and uncertainties inherent to the manufacturing environment, and captured by analysing the prediction efficiency of manufacturing processes and by analysing unpredictability of manufacturing system performance. The last symptom in this class is the existence of manufacturing flow turbulence arising due to the interactions among system performance, lead time, process structure and manufacturing system configurations.

The next section now describes the symptoms observed from the physical situation.

### 5.3.3 Symptoms observed from the physical situation

Based on the research of Frizelle & Suhov (2011) and Espinoza et al. (2012) complex system theory describes a complex system as a system that is composed of many components and exhibits hierarchy and self-organisation arising due to the dynamic interaction of its components from this viewpoint, contains complexity symptoms that can be perceived through analysing system’s physical situation:

- **System element information:** Increased variety, quantity, and information content of system elements.
- **System element interdependence:** The significance of system element interrelations and interdependencies.

These symptoms can be searched within the various aspects of the system, meaning system configuration, material flow patterns, control and information flow patterns, intrinsic process hierarchy, etc., and are often analysed by means of heuristics including enumeration and classification and coding, as well as the methods derived from graph theory. Enumeration based approaches try to capture information content of the system by counting system-related elements, e.g., resources, products, customer orders, tasks, etc. in a systematic manner.

### 5.3.4 Symptoms observed from human perceptions

As stated, complexity is subjective, making it dependent on the system being considered and on the view of the human spectator (Liang & Gou, 2021). In view of that, the last class of symptoms contains complexity indicators which can be perceived by humans. In this class, the symptoms are classified into four sub-groups:

- **Technological complexity:** Indicating the complexity of the underlying technology used to perform system related activities. (Schöttl & Lindemann, 2015)
- **Knowledge complexity:** Representing the domain-specific knowledge and decision-making complexity. (Schöttl & Lindemann, 2015)
- **Shadow systems:** Meaning that people don’t use the formal modes of the organization which are called legitimate system to handle the business of the organization but use other informed ways which organization did not make any provision and acknowledge to handle business. (Liang & Gou, 2021)
- **Information overload:** Representing the increasing flow of information that the human brain must process to be able to navigate in complex systems (Turner & Baker, 2019, Phillips Wren & Adya, 2020)

The mentioned aspects show that symptoms of the human perception can be related to the subjective source of complexity.

The introduced symptoms are now summarized in the following Table 6.

*Table 6: Complexity symptoms in manufacturing systems*

| **Symptom category** | **Symptoms applied in the assessment of manufacturing system complexity** |
|---|---|
| Nonlinear behaviour | • Repeating patterns in long-term system behaviour<br>• Sensitivity to initial conditions<br>• Emerging dynamic behaviours |
| Operational uncertainties | • Increased amounts of information<br>• Operational dynamism<br>• Uncertainty in handling increased product variety<br>• Uncertainty associated to the predictability of manufacturing operations |
| Physical situation | • Increased variety, quantity, and information content of system elements.<br>• The significance of their interrelations and interdependencies. |
| Human perception | • Technological complexity indicating the complexity of the underlying technology used to perform system related activities.<br>• Knowledge complexity representing the domain-specific knowledge and decision-making complexity.<br>• The existence of shadow systems<br>• Information overload |

According to Sheard & Mostashari (2010) the consequences of these complexity symptoms can include if they remain unmanaged:

- Increases in product life cycle costs
- Difficulty of getting engineering changes made
- Difficulty in servicing, leading to many failure modes
- A complex supply chain, resulting in management and logistical problems
- The need for a complex, and therefore costly, design process

The notions described in Table 6 are well summarized by Figure 17 which is based on introduced properties of manufacturing complexit and building on the research of Gorzen-Mitka & Okreglicka (2014) and Sheard & Mostashari (2010).

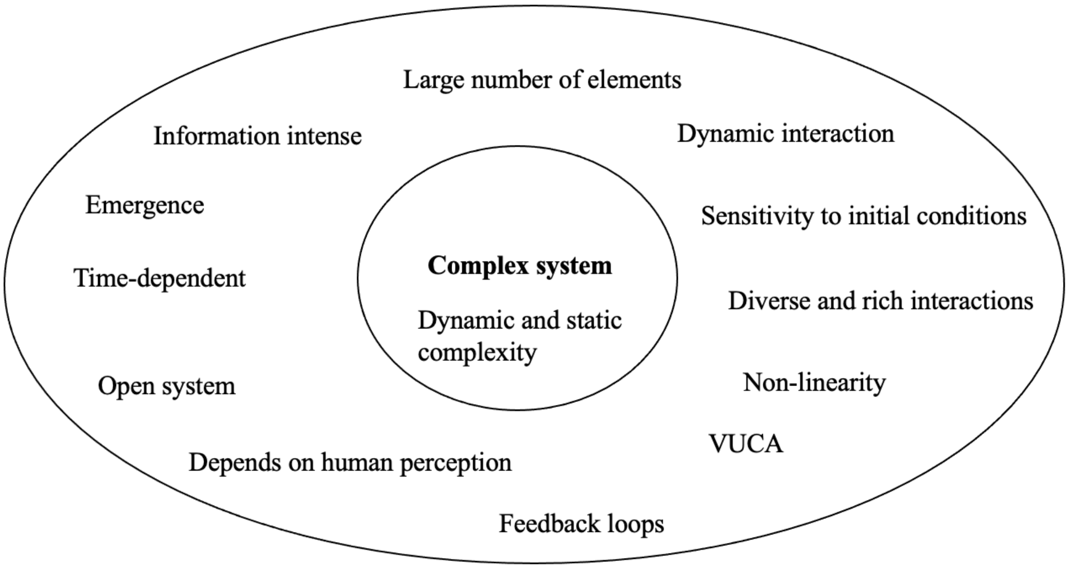



*Figure 17: Characteristics of complex industrial systems*

Figure 17 shows that complex systems are characterized by a wide variety of characteristics which must be understood in the context of complex manufacturing systems.

Consequently, this thesis rejects the definition of objective complexity sources and takes the stance that complexity symptoms must be understood and managed by human decision-making activity.

Consequently, system complexity shall be regarded as a function of the inherent complexity potential of a system and the perception capacity of the human observer. (Schöttl & Lindemann, 2015) This notion is underlined by the functionality of MITRE's Enterprise Systems Engineering Profiler tool, which is a self-assessment tool for system complexity, there six of the eight octants have nothing to do with the technical system, they deal with stakeholders, scope, and acquisition context.

These aspects fall outside the standard scope of engineering and if they are not properly addressed, complex technical solutions like CPS are likely to fail. (Sheard & Mostashari, 2010, Stevens, 2008)

To underline this notion the next section now further elaborates on how these symptoms translate into complexity manifestations in systems engineering practice.

### 5.3.5 Complexity symptoms in systems engineering practice

Based on the work of Rosser (2019), the following complexity manifestations can be observed in engineering practice:

- **Difficulty to agree on a definition of the problem:** Can be caused by the existence of multiple perspectives and stakeholders.
- **A wide range of possible responses that may affect the problem, but none that solve it completely:** Indicates a multivariate problem which must be balanced to provide acceptable outcomes for all aspects rather than optimizing for one.
- **Asking the same question or taking the same action multiple times can produce different results:** Suggests emergent behaviour which may or may not be adaptive or intentional.
- **Difficulty in defining what "done" or "good enough" means:** Often related to many participants, many perspectives required that are not completely aligned.
- **Problem does not respond to proven processes, methods, or approaches:** Can be related to emergence, or to processes and methods that don't account for the entire scope.
- **Risks persist despite attempts to mitigate:** May indicate opacity of important variables, hidden dependencies or competing risks which must be balanced.

According to Rosser (2019) and Liang & Gou (2021) practitioners are likely to have experienced the manifestations described above but may not necessarily associate them with complex systems science.

Highlighting the relationship between common intractable problems in the engineering of industrial systems and the impacts of complexity enables the practitioner to recognize and respond to the impacts of complexity in their work and is a strong indicator for the relevancy of subjective complexity sources and the subjective perspective on complexity.

To achieve this goal the next section now introduces and discusses methods to assess complexity in manufacturing systems.

## 5.4 Methods to assess complexity in manufacturing systems

The previous section has identified the symptoms of complexity which exist within several dimensions of a manufacturing system. This chapter now examines a range of prominent assessment and analysis methods for capturing these symptoms. By following a classification scheme mainly based on the taxonomy presented by the work of Alkan et al. (2018) and Efthymiou et al. (2016), these methods are now briefly investigated according to their respective theoretical origins:

- Chaos and nonlinear dynamics theory
- Information theory
- Heuristics
- Graph theory
- Surveys

Consequently, the topic of chaos and nonlinear dynamics theory is described first.

### 5.4.1 Chaos and nonlinear dynamics theory

Chaos and nonlinear dynamics system theory is a mathematical area with increasing interests in the fields of physics, engineering and social sciences. In the literature, the methods derived from chaos and nonlinear dynamics theory are often employed to measure complexity through analysing symptoms connected to the system's dynamic behaviours. A dynamical system is a time-depending multi-component system of elements with local states determining a global state of the whole system. (Efthymiou et al., 2016)

In a planetary system, for example, the state of a planet at a certain time is determined by its position and momentum. The states can also refer to moving molecules in a gas, the excitation of neurons in a neural network, nutrition of organisms in an ecological system, supply and demand of economic markets, the behaviour of social groups in human societies, routers in the complex network of the internet, or units of a complex electronic equipment in a car. (Mainzer, 2004, Efthymiou et al., 2016)

The dynamics of a system, i.e., the change of system's states depending on time, is represented by linear or nonlinear differential equations. In the case of nonlinearity, several feedback activities take place between the elements of the system. These many- bodies problems correspond to nonlinear and non-integrable equations with instabilities and sometimes chaos. (Mainzer, 2004)

These methods include phase space reconstruction, maximal Lyapunov exponent testing and bifurcation diagrams. (Efthymiou et al. (2016), Subramanian et al. (2010) and Alkan et al. (2018), Mohanta et al. (2020) and Gao & Xu (2021)

According to Efthymiou et al. (2016), the methods based on chaos and nonlinear dynamics theory often offer valuable understandings of the system behaviours, visualises the effect of system parameters on the key performance indicators, and depicts the sensitivity of the system. However, a set of limitations can be established.

Modern manufacturing systems often exhibit stochastic events (e.g., machine breakdowns) rather than deterministic chaos. However, tools and methods developed based on this theory, are not able to capture and analyse such stochastic events.

Moreover, only maximal Lyapunov exponents testing provides a quantitative measure for chaos within the manufacturing system, other methodologies are limited and offer only schematic analysis for the dynamic system behaviours. (Alkan et al., 2018)

Furthermore, the approaches used for approximation of the Lyapunov exponents require relatively large datasets and they are highly sensitive to the fluctuations in the external factors such as measurement errors and noise (Efthymiou, 2016).

In summary, the theory of chaos and nonlinear dynamics can be potentially considered as an highly valuable tool in behavioural analysis of manufacturing systems.

However, these methods require a costly measurement-phase, and they are not able to capture stochastic complexity sources, therefore it is still questionable as to whether these tools are a practical solution for real industrial environments. (Alkan et al., 2018)

The next section now describes the method of information theory.

### 5.4.2 Information theory

Information theory, principally proposed in Shannon's study of communication theory, considers entropy as the degree of ambiguity associated to the outcomes of a random experiment. In the manufacturing domain, this approach is used to capture the following symptoms:

- Scheduling and observation-based information content of resource or queue states
- Deviation between scheduled and actual states of the resources
- Uncertainty in handling product variety with the context of risk factors related to the operator choices
- Unpredictability of manufacturing processes and manufacturing performance indicators

These methods include Shannon entropy, Kolmogorov complexity and Lempel-Ziv analysis of finite time series and computational mechanics. (Efthymiou et al., 2016, Alkan et al. 2018, Ding & Sun, 2012, Lempel & Ziv, 1976, Zupanovic et al., 2010, Swenson, 1988, Fortnow, 2010, Li, 2021).

Information theoretic measures propose a seemingly objective way for quantifying both static and dynamic complexity of manufacturing systems. Nevertheless, a set of problems hold back the applicability of the information theory. According to Efthymiou et al. (2016), information theoretic measures alone are insufficient to link complexity with the manufacturing system performance.

Information theoretic complexity measures provide a single complexity value which provides an insufficient level of granularity to determine where efforts should be focused to make improvements. Furthermore, as there is a subjectivity associated with the selection of resource and queue states, information theoretic measures may struggle to explain perceived complexity, e.g., interactions between human and machine.

Kolmogorov complexity, Lempel-Ziv analysis method heavily depend on the observed performance time series length (Efthymiou et al., 2014). Also, this approach requires a common time series length for the comparison of dynamic complexity of different manufacturing systems, which may not be the case in many situations (Efthymiou et al., 2016). Computational mechanics approach, on the other hand, suffers in terms of practicality, as it requires relatively big amount of data necessary to analyse dynamic complexity.

The next section now describes the method of heuristics.

### 5.4.3 Heuristics

Heuristics based complexity assessment approaches are close to industrial practice where they attempt to capture the overall information content of a production system using user-subjective or counting based information collection techniques. These methods can be a valuable solution when data availability is limited, and resources are scarce. Heuristics measures include Enumeration, product and process complexity and complexity management frameworks. (Efthymiou et al., 2016, Gorzen-Mitka & Okreglicka 2014, Fathi et al., 2016, Alkan et al., 2018, Schöttl & Lindemann, 2015)

Due to their subjective nature, heuristics-based approaches build on an inherently subjective vision of manufacturing system complexity, and they potentially are unable to analyse complicated connections within a system in all objective detail. (ElMaraghy et al., 2012)

Metrics of heuristics are thus heavily dependent on the industrial domain or specific focus that they are designed for, thus, the applicability of heuristics-based approaches over different types of production systems and focuses is often limited.

In conclusion, heuristics-based approaches provide an intuitive and helpful view regarding complexity associated with the physical situation, however, due to its subjective nature, it is debatable as to whether these measures reflect overall system complexity very accurately.

The next section now describes the method of graph theory.

### 5.4.4 Graph theory complexity metrics

According to Zenil et al. (2018) networks, which are used extensively in science and engineering, are often complex when representing static and dynamic data where edges are relations among objects or events. It addresses the challenge of quantifying this complexity to deal with such complexity and eventually steer such objects in educated ways. Graph theory provides a basis for investigating the entities and their relationships within a networked system.

For example, Chryssolouris et al. (2013) propose a complexity measure called network complexity, in which graph theory is used to produce an adjacency matrix which represents the connection between product, process, and resource domains. The vertex degree is then used to assess the coupling between these domains. ElMaraghy et al. (2014) on the other hand developed a complexity model based on the graph theory which incorporates information content of the system represented by characteristics of its layout.

The next section now describes the method of surveys.

### 5.4.5 Surveys

Questionnaires, surveys, and interviews attempt to provide insights on how humans perceive manufacturing systems during their lifecycle. They can be used to analyse bottlenecks and to get indications of potential improvements by flagging the interrelating complexity concerns. Although survey-based approaches can capture the perceived level of complexity, these approaches cannot be used in the evaluation of system designs since no physical mock-up or process trials are available. Also, they are limited to the questionnaire-stage and their results are dependent on the subjective interpretation of the interviewees. (Alkan et al., 2018, Calinescu et al., 1998)

## 5.5 Complexity types, symptoms, and methods overview

The following Table 7 now summarizes the described method categories and methods applied in each category.

*Table 7: Complexity types, symptoms, and methods*

| **Method category** | **Methods applied in the assessment of manufacturing system complexity** |
|---|---|
| Chaos and nonlinear dynamics theory | • Phase space reconstruction<br>• Maximal Lyapunov exponent testing<br>• Bifurcation diagrams |
| Information theory | • Shannon entropy<br>• Kolmogorov complexity<br>• Lempel-Ziv analysis of finite time series<br>• Computational mechanics |
| Heuristics | • Enumeration<br>• Product and process complexity<br>• Complexity management frameworks |
| Graph theory-based metrics | • Network complexity<br>• Graph-based complexity metrics |
| Surveys | • Questionnaires<br>• Surveys<br>• Interviews |

After summarizing the different method categories and corresponding methods to assess industrial system complexity, these results are now integrated with the already defined complexity types and their respective symptoms in a coherent overview as illustrated in Figure 18.

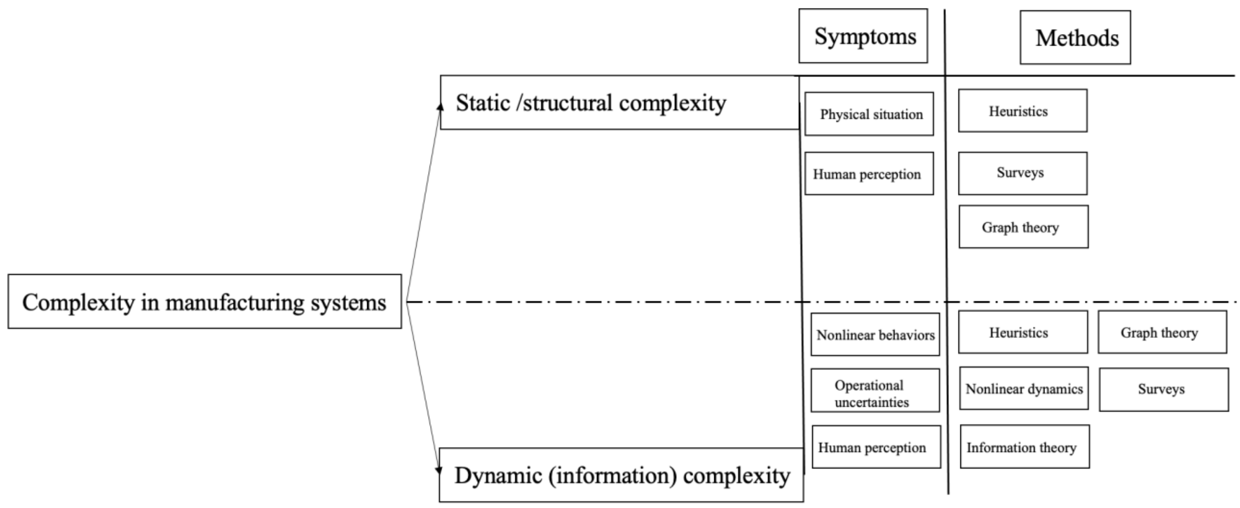



*Figure 18: Complexity symptoms and assessment methods in complex industrial systems*

Figure 18 makes visible that complexity symptoms of the physical situation and human perception are attributed to static / structural complexity. Symptoms like nonlinear behaviour, operational uncertainties and human perception are attributed to dynamic complexity.

It is furthermore shown through the analysed literature that three methods can be applied to assess both static and dynamic complexity types:

- Heuristics
- Graph theory
- Surveys

It is also shown that alle three methods come with their own unique benefits and limitations when it comes to analyse the complexity of an industrial system.

In the light of this statement and after introducing and discussing different methods to assess complexity in industrial systems, the next chapter now covers the topic of strategic management and heuristic strategic management tools and techniques as a baseline to define the concept of strategic complexity management in later sections of this study.

# 6 Strategic management & complexity management

The terms strategy, strategic management, strategic complexity management, heuristics, complexity management and different complexity management frameworks in the form of the Cynefin Framework, Schuck´s Control Matrix and the Stacey Complexity Matrix are now defined and discussed in this chapter and the relevance of heuristics as a well-suited assessment method for complexity management tools is introduced, discussed and illustrated. In a first step, the term strategy is defined in the next section.

## 6.1 Strategy

Even though difficult to define in a precise and universal way, strategy is a central concept for the field of strategic management, as it directly concerns the planning process of the deployment of resources (e.g., investment) to achieve a given set of objectives (e.g., return on investment). (Berisha Qehaja et al., 2017a)

Strategies shall be defined as a means for companies to generate a competitive advantage. In a business context, strategies are assumed to not be absolutely formulated or formed, also are they not purely realized or intended.

Companies do not only create new strategies but also modifying existing ones, based on facts as well as on the intuition and experience of senior managers. (Jofre, 2020)

This is supported by Vieweg (2015) who states that the so-called *management by options* is a well-suited approach for complexity management, where strategy means good preparations and reliable preliminary work to be well prepared at the right moment in time.

Intuitively, it can be concluded, that in strategic management the process of strategy selection is of utmost importance to the decision-maker.

In the process of strategy selection, as indicated by the previous section and explicitly stated by David & David (2017), decision-makers can never consider all feasible alternatives that may be or not be beneficial to the firm because there are an infinite number of possible actions and infinite ways of implementations that exist in a dynamic economic environment.

Therefore, a manageable set of the most attractive alternative strategies is extracted, developed, examined, prioritized, and selected. This process is primarily based on the utilization of decision-making frameworks that allow to identify, evaluate, and select strategies in the process of strategic management in a combination of managerial intuition and analysis. (Afonina, 2015)

## 6.2 Strategic management

Strategic management as a discipline now focuses on the development and implementation of strategies. It entails analysis, decisions, and actions as core components. It thus focuses on the direction of organizations, companies and businesses and the application of theories, frameworks, tools, and techniques to assist the decision-makers in the implementation of the planning, thinking and design process of strategy for organizational purposes, most of the time being the purpose of creating competitive advantage. (Berisha Qehaja et al., 2017a, Berisha Qehaja et al., 2017b, Jofre, 2020, Sammut-Bonnici, 2015, Afonina, 2015)

### 6.2.1 Strategic management perspectives

Strategic management can therefore be defined as a process consisting out of the steps: evaluation, planning and implementation of a business situation through strategy to improve the competitive advantage of the firm. (Sammut-Bonnici, 2015, David & David, 2017)

These steps are now conducted from two different perspectives, the company internal and external perspective.

The internal perspective is represented by the resource-based view, which states that the internal resources and capabilities of the firm are the critical determinant for success. Only if these resources are unique, difficult to copy and hard to imitate the firm will maintain its competitive advantage. Examples for company internal capabilities for example are development of innovative technology, reducing time to market of products, creation of more efficient production or distribution channels and the ability to deploy current and future technologies effectively and efficiently. (Sammut-Bonnici, 2015, Ghani et al., 2020)

The external perspective is the environmental view of the industrial organization which assumes that the external environment determines the strategic actions a company can deploy. This shows that strategic management is based on the evaluation and analysis of company internal and external factors and requires to consider both internal and external factors in the strategic analysis of the firm. (Sammut-Bonnici, 2015, Ghani et al., 2020) Examples for company external factors are summarized under the acronym of PEST: political, economic, socio-cultural, technological. (Ghani et al., 2020)

Figure 19 now provides an overview of the applied definition of strategic management and its perspectives.

| Strategic Management | |
|---|---|
| *Internal perspective* | *External perspective* |
| **Resource & capability-based view** | **Environmentally-based view** |

*Figure 19: Perspectives of strategic management*

Based on this it is now possible to introduce the process of strategic management.

### 6.2.2 The process of strategic management

Based on the work of Freund (2013) and David & David (2017) the process of strategic management can be defined as illustrated in Figure 20.

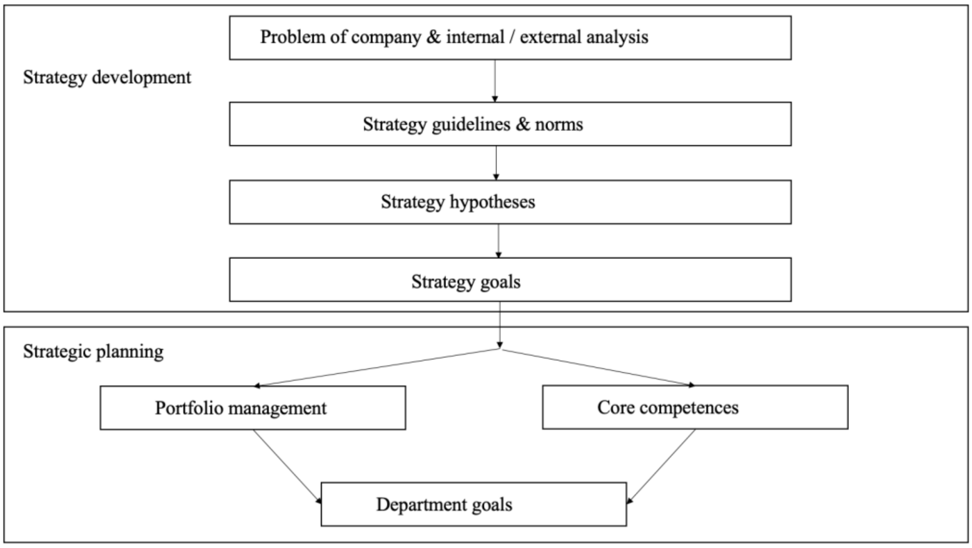



*Figure 20: Strategic management process*

Figure 20 illustrates the strategic management process step by step, starting with the development of the strategy. The step of internal and external analysis of the corporate environment was already described in detail.

The so-called strategy guideline plays an important role in the next step. It sums up the content of the strategy selection process, which ultimately results in the declared direction of the strategy from a multitude of conceivable strategic options, which shall be defined as a “norm strategy”.

According to Freund (2013) it is important to differentiate very precisely between a corporate vision and a strategy guideline. If a vision tends to reflect the ambition of a company ("we want to become a leading company in the ... industry") and therefore has a very general and comprehensive validity, the strategy guideline must serve as a central anchor point for all strategic building blocks and contains the derived considerations from the internal and external environmental analysis.

This suggests starting points for competitive advantages and already indications of a possible implementation into practice. The strategy guideline has the important task of concisely articulating the normative core of a strategy and the decisions of the management in one precise sentence and in this way anchoring them in the minds of the stakeholders who partake in the strategy. In addition to its meaning in terms of content, a norm strategy has thus a significant communicative dimension in the development and implementation process of strategy. (Freund, 2013, David & David, 2017)

Based on this more detailed strategy hypotheses can be developed which then lead to precise strategic goals.

After this is achieved the process of strategy development ends and the process of strategic planning begins. As stated by Freund (2013) it occupies a position between strategy development and organizational implementation on the one hand, but also between strategy development and the innovation process on the other.

It must therefore ensure that a strategy is expressed at a functional level in organizational structures and the alignment of core competencies, and at the same time it must ensure that the right innovation focuses are set as part of a product portfolio. In this light, the next section describes strategic management tools & techniques as a practical application to manifest the strategy process of strategic management.

## 6.3 Strategic management tools & techniques

The applied definition of strategic management and the strategic management process make visible that SMTTs play a vital role in the evaluation and planning process of the strategy development process in strategic management. The term *strategic tool* is to be regarded as a generic term for any method, model, technique, tool, technology, framework, methodology or approach used to heuristically facilitate strategy. (Afonina, 2015, Berisha Qehaja et al., 2017b)

In general, SMTTs are applied by decision-makers to increase operational performance through achieving the following goals: Investigate external and internal cost of products, services, production etc., obtain information (for example market information, knowledge management) and predict and assess various aspects of OP. (Afonina, 2015)

In today´s VUCA market environments decision-makers often must deal with a wide variety of decision-making problems from many directions simultaneously. SMTTs can provide valuable help to reduce the complexity and uncertainty in decision-making situations and are thus becoming increasingly attractive and important to achieve rational and knowledge-based strategic decision-making. (Nouri et al., 2017, Berisha Qehaja et al., 2017a)

This aspect is also underlined by the wide variety of application areas of SMTTs which for example include operations management, information technology management, productivity, and efficiency management. These aspects show, that SMTT are not only important for analytical purposes but can also provide business strategy and help in maintaining competitive advantage. (Berisha Qehaja et al., 2017a, Afonina, 2015, Nouri et al., 2017, Berisha Qehaja et al., 2017b)

SMTTs are also adhering to the practical need that strategic decision-making process must be very concise and direct, adhering to the ideal that in order to communicate the strategy, there must be exactly one declared strategy and, derived from it, action plans for the functions in the company which can be summarized on no more than one A4 page in size. (Freund, 2013)

This indicates that strategic management is to be regarded as an interpretative, interactive, and meditative process that is, even though closely connected, not interchangeable with the process of strategic thinking, leadership and strategic planning. (Peressier, 2012, Freund, 2013)

Figure 21 illustrates this relationship in more detail by showing that SMTTs are applied at the strategy level of strategic management which guides the subordinated level of implementation via decision-making. Strategic planning and strategic thinking are located at implementation level of the management of a system and are regarded as expressions of leadership.

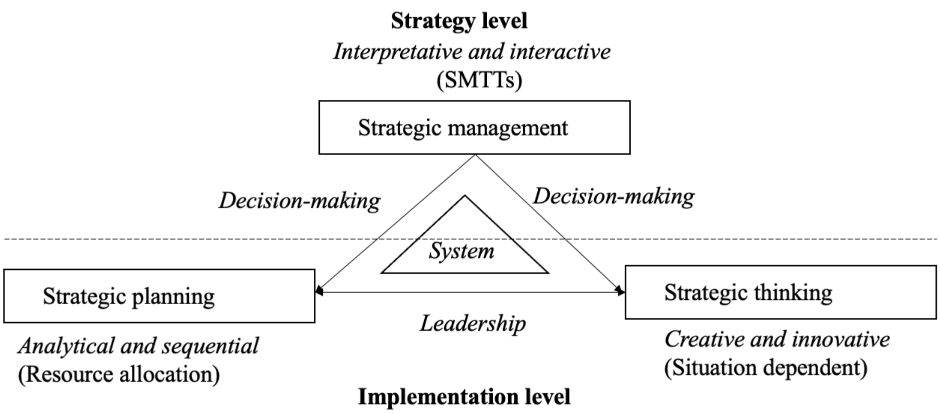



*Figure 21: SMTTs in the context of strategic management*

Based on this, the next section now introduces a selection of SMTT examples.

### 6.3.1 SMTT: Examples

It is important to mention that the list of existing SMTTs has been increasing over the last two decades. Various tools and techniques have been provided to help managers identify the decisions related to strategic planning.

In correspondence to the increase of existing SMTTs, Afonina (2015) shows that SMTTs are consistently applied in over 50% of situations by decision-makers, some prominent SMTT examples are:

- SWOT analysis
- Cost-Benefit analysis
- PEST analysis
- Benchmarking

To illustrate the functioning of a SMTT the SMTT "SWOT analysis" in the form of the SWOT strategic matrix is now described and illustrated. SWOT analysis was first designed and introduced in 1960 by Stanford´s research institute and since 1975 was widely used as an analytical framework for developing company strategies and it is still applied in current research applications. (Fahrhangi et al., 2021)

The SWOT matrix properly analyses the internal strengths and weaknesses as well as external threats and opportunities of the company to guide the future expected strategies. This matrix, as shown in Figure 22, is a useful tool for strategic planning of strategic management and a fundamental basis for identifying conditions and planning future methods which are necessary for strategic observation.

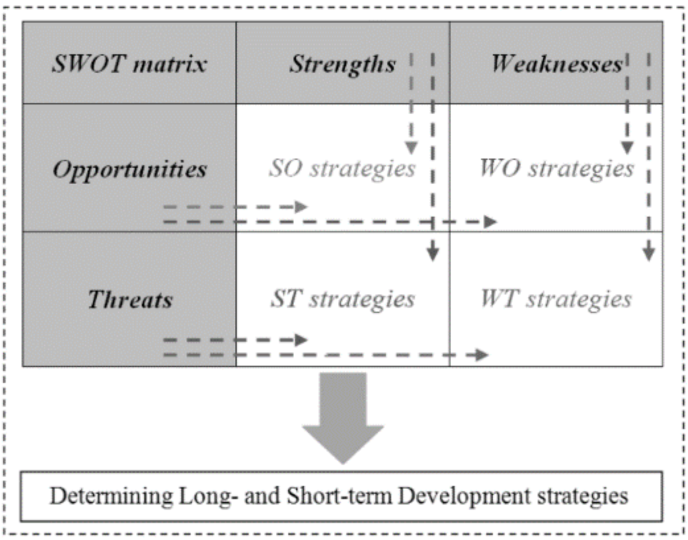



*Figure 22: SWOT matrix (Fahrhangi et al., 2021)*

Figure 22 shows, that in this analysis, the internal and external factors are evaluated first, which is called the input stage, and the information required for devising strategies is determined. During the second stage, which is called the comparison stage, all the possible strategies are considered through developing a SWOT matrix. The objective of the SWOT matrix is to determine all applicable strategies and the best strategy is not sought at this stage. Strategists then use this matrix to create and introduce one of four kinds of generic norm strategies (SO, WO, ST, and WT strategies). (Fahrhangi et al., 2021)

Another prominent example for a matrix based SMTTs is the BCG Matrix, which is now illustrated in Figure 23 and represents a SMTT often applied for the complex task of strategic product portfolio management.

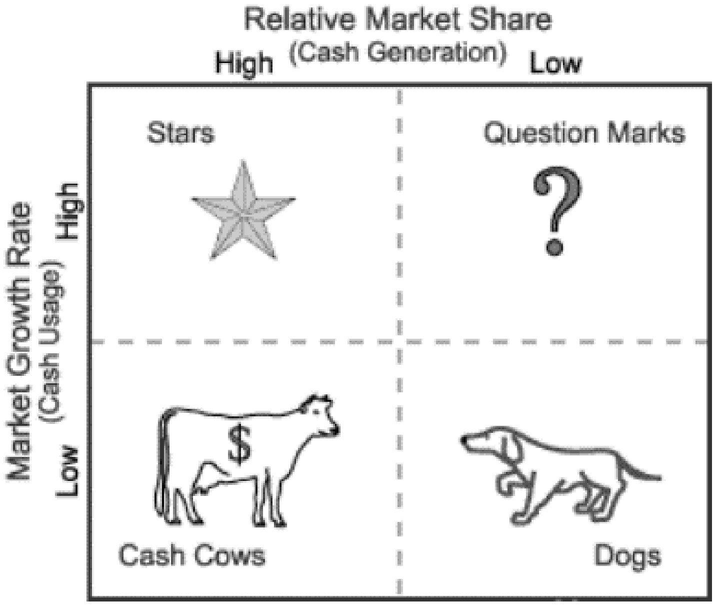



*Figure 23: BCG matrix (Mohajan, 2018)*

Both provided examples share a generic matrix format with a simple two-dimensional analysis, which both reflect the company internal and external view. (Mohajan, 2018)

Both examples allow to effectively and categorize decision-problems and to deduct first norm strategies as an answer in a holistic way.

This is supported by the research of Afonina (2015) who shows that in general managers prefer to use holistic and heuristic tools and techniques. It can consequently be shown that SMTTs are heuristic tools that are valuable for decision-makers to provide strategic aid in decision-making, and which decrease the complexity of a decision- making situation. This statement is supported by Törngren & Grogan (2018) who state that in the context of CPS the application of strategic management in relation to the organization is essential since future CPS will require new competences, roles, and responsibilities.

This aspect is especially important in the light of *Conway´s Law* which allows to state that a system´s architecture parallels its parent organization structure in terms of complexity since organization's structures, problem solving routines and communication patterns determine the space in which new solutions can be created. (MacCormack et al., 2012)

According to David & David (2017) it is also important to acknowledge that the decision-makers themselves, not strategic tools like SMTTs, must always be responsible and accountable for strategic decisions.

To put the presented information into the context of complexity, the next section introduces the definition of complexity management.

## 6.4 Defining complexity management

According to Gorzen-Mitka & Okreglicka (2015) the "complex" view of reality is important in understanding the activities of an organization. In the context of industrial systems and according to Vogel & Lasch (2016) complexity management in the manufacturing company requires identification and controlling of complexity drivers because complexity drivers lead to increasing complexity in manufacturing.

A complexity driver shall be defined as a condition that causes subsequent conditions or decisions to occur because of its own occurrence. Consequently, a complexity driver is responsible for a situation or condition and at least has an impact on it. (Vogel & Lasch, 2016)

Complexity management is to be regarded as highly relevant topic for modern industrial systems management because projects related to complex systems exhibit Flyvbjerg's performance paradox with the level of system performance contrasting with the levels of importance of such projects actually receive in the respective organizations. (Maylor & Turner, 2017)

Complexity is rated as one of the main reasons for this performance paradox, reinforcing the importance of developing applicable complexity management tools and to increase complexity management implementation in practice. (Flyvbjerg et al., 2003, Maylor & Turner, 2017)

The inclusion of complexity in the scientific and management discourse for complex manufacturing systems like CPS is therefore a natural consequence but it is shown that not many companies have implemented a complexity management approach, or they do not know if the used complexity management strategy and methods are efficient and adequate. (Vogel & Lasch, 2016, Törngren & Grogan, 2018)

According to Maylor & Turner (2017) complexity management is more focused on the idea of a "complexity of", subjective complexity representing the lived experience of managers of what they termed "complexity" than on a rationalist approach to the phenomenon with the goal of objectifying complexity.

Consequently, the complexity of a system is to be regarded as the independent variable, with the managerial response being a function of that complexity.

In this regard complexity management assumes that if this independent variable is well understood, then it is possible to make an input in complexity management practice. (Maylor & Turner, 2017)

These statements are now illustrated in Figure 24.

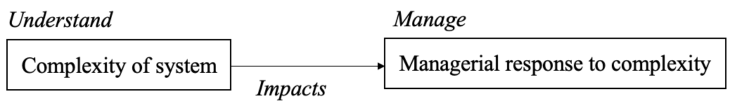



*Figure 24: Basic assumptions of complexity management*

Based on Figure 24 and according to Kirchhoff et al (2003) the tasks of complexity management are now defined as the following:

- **Considering and solving problems:** Resulting from the variety, the range, and the dynamics of internal and external elements and relations of the company or system and its environment.
- **Observing the problems of actors**: Subjectively dealing with complexity, expressing themselves in thinking and behavior patterns, perceptions, decisions, and actions as well as in management and organizational structures.
- **Integrating different individual measures**: Dealing with complexity into a synergetic strategic framework.

In the light of the tasks of complexity management and according to Jackson (2019) it can now be stated that the core task of complexity management is thus to tackle so called *organized complexity*, which is contrasted by *organized simplicity* and *unorganized complexity*.

Consequently, the concept of organized complexity is defined in more detail in the next section.

### 6.4.1 Organized complexity

Based on Jackson (2019) the concept of organized complexity is illustrated by Figure 25.

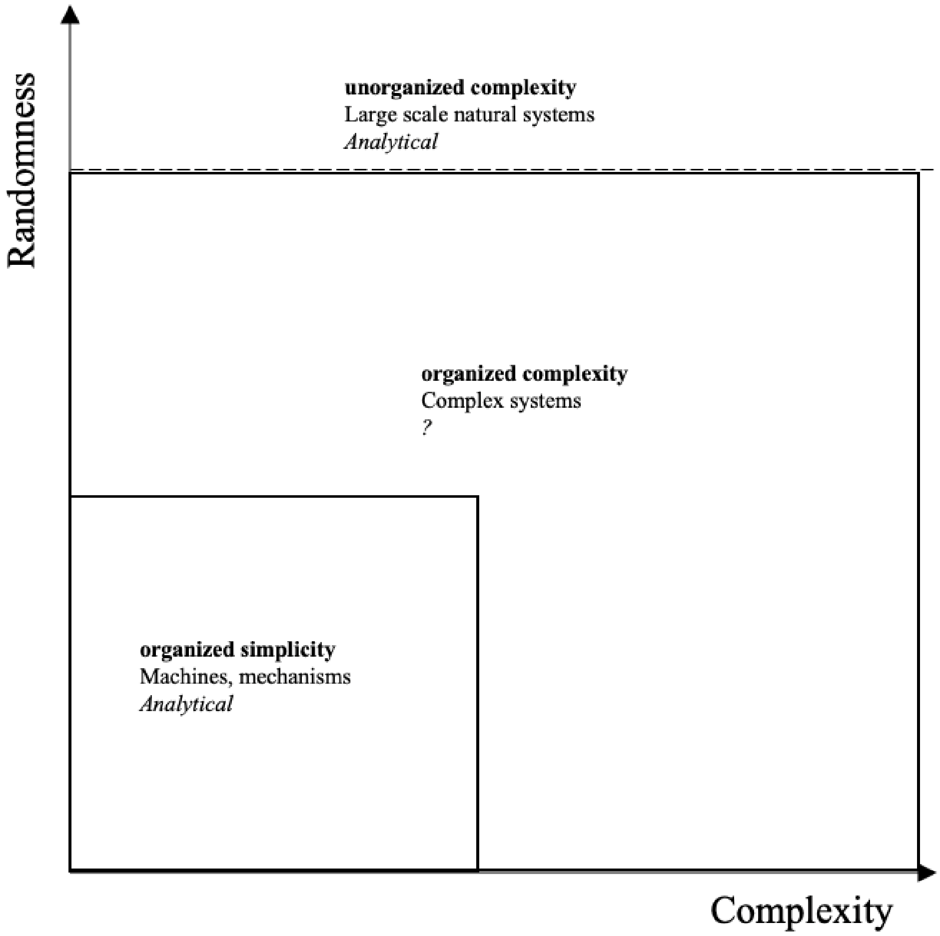



*Figure 25: Organized complexity*

Figure 25 shows that three general type of complex system types can be differentiated in the form of organized simplicity, organized complexity, and unorganized complexity.

As stated by Jackson (2019), Heino et.al (2021) and Wolfram (2002) traditional science is primarily able to tackle organized simplicity (very small number of objects that behave in predictable ways, e.g., mechanisms and machines) via for example, differential equations, and unorganized complexity (very large numbers of components exhibiting a high degree of unpredictability, e.g., aggregates, gases, and populations) via for example, Bayesian statistics.

It can be noted that both organized simplicity and unorganized complexity represent the extremes of the scales of randomness and complexity.

As Jackson (2019) and Heino et.al (2021) furthermore state, most real-world problems are located somewhere in between both and are situated in organized complexity.

One core example for this category is, among others, especially the area of problems associated with modern technology, like Industry 4.0 and CPS, as these systems exhibit neither organized nor unorganized complexity and models are still lacking to manage the complexity of these systems. (Collier, 2010, Jackson, 2019, Törngren & Grogan, 2018)

Managing organized complexity shall thus be the central goal of strategic complexity management.

Collier (2010) additionally distinguishes in the context of organized complexity between four types of dynamical systems differentiated by their degrees of complexity and organization. Complexity in this regard is defined as the number of independent pieces of information needed to specify a system.

Organization now characterizes the extent of the interrelations among the components of the system in terms of their number, scope, and dynamics. Through these four different types of systems result as displayed in Figure 26, as displayed in Collier (2010).

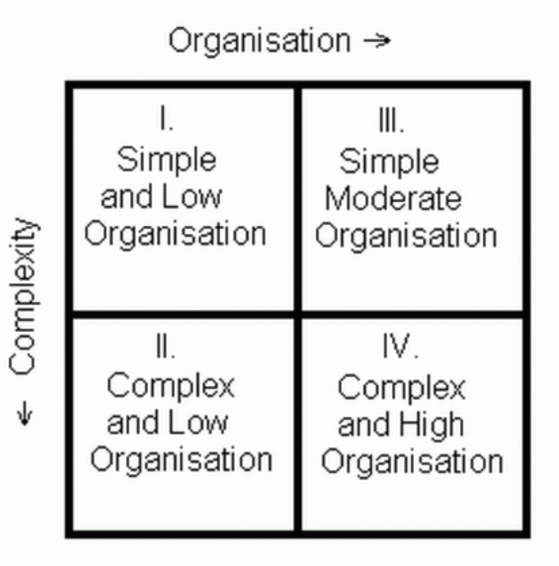



*Figure 26: Types of complex systems (Collier, 2010)*

Colliers (2010) states that type I systems are exemplified by single element or decomposable multi-element systems on the edge to organized simplicity, e.g. one machine or few machines.

Type II systems are defined by statistically specified systems at or near to equilibrium as bounded components of large-scale natural systems on the edge to unorganized complexity (e.g. gases, fluids, populations).

Type III systems are sufficiently well constrained but non-linearizable, difficult to decompose multi-element systems, with few or nonemergent effects, e.g. many machines, also positioned on the edge of organized simplicity.

Type IV systems are not tractable and decomposable. They can show emergence and openness and can't be understood except through a holistic treatment and heuristic understanding. In comparison to systems of types I and III, whose organization, if any, is fully determined by their initial internal and boundary conditions, type IV systems can thus produce novel organization, emergence, through self-organizing processes.

In comparison to type II systems, whose organization is entirely imposed and determined by external boundary conditions like natural laws, type IV systems contribute internally to their organization.

This makes visible that many real-world business systems and their respective decision-making problems are assumed to be situated in type 4 systems and are thus assumed to be inherently non-linear with many parameters and are shaped by an interplay of internal and external dynamics.

It has been shown in this study that especially Industry 4.0 systems like CPS are very likely to fall under the category of type 4 systems, as their core characteristics according to the IKTF are interoperability, heterogeneity, modularity, compositionality and increasing complexity.

This leads to the circumstance and intuitive assumption that some or even most CPS systems, like smart manufacturing systems, can be expected to be too complex to be capable of exact analysis by traditional scientific means.

As shown in Collier (2010), Figure 27 now reflects this statement.

| | **Equation:** | Algebraic | Ordinary Differential | Partial Differential |
|---|---|---|---|---|
| **Linear Equations** | One Parameter | Trivial | Easy | Difficult |
| | Several Parameters | Easy | Difficult | Intractable |
| | Many Parameters | Intractable | Intractable | Impossible |
| **Nonlinear Equations** | One Parameter | Very Difficult | Very Difficult | Impossible |
| | Several Parameters | Very Difficult | Impossible | Impossible |
| | Many Parameters | Impossible | Impossible | Impossible |

*Figure 27: Complexity vs. traditional scientific analysis (Collier, 2010)*

As defined type 4 systems like some CPS architectures can be expected to be non-linear and have many parameters, which leads, as displayed in Figure 27, to the circumstance that they are unsolvable via traditional analytical methods. This reenforces the statement made namely that there is a distinct gap in methods of analysis when it comes to the study of organized complexity in comparison to unorganized complexity or organized simplicity.

It is nevertheless important to mention that recent research introduces approaches based on artificial intelligence (AI) and neural networks (NN) build on neural ordinary differential equations which aim to solve control problems of complex dynamic systems in a direct response to those problems being analytically and computationally intractable. (Böttcher et al., 2022)

These advances might lead to real-world applicable solutions for system optimization in the future, for example in supply chain optimization. The core challenge to use such approaches as intended lies in the circumstance that it must first be provided with precise information on system dynamics in the first place.

This information is then utilized to determine which areas need optimization. Users must additionally provide information on the system's initial status, this could be information such as current stock levels, and its desired target status or the requirement to replenish stock to certain levels while minimizing the use of resources. (Böttcher et al., 2022)

This shows that even most recent AI and NN approaches require that the system to be optimized is at least partially well-known so that input variables can be determined correctly and underlines the quasi-paradoxical dilemma that occurs when advanced traditional scientific methods are to be applied on problems of organized complexity, namely that the system and its dynamics must already be well-known to some degree in advance.

One possible explanation for the phenomenon of the apparent non-applicability of traditional science in organized complexity is introduced by Wolfram (2002) in the form of the *Principle of Computational Equivalence*. This principle states that a system´s behaviour can be thought of as corresponding to a computation (or intelligence) of equivalent sophistication. This infers that there are systems which are executing computations that are at least as complex as the computations (or intelligence) that can be conducted by the observing human activity via mathematics or computation. This leads to the conclusion that many complex systems are in fact at least temporarily irreducible, and outcomes cannot be exactly predicted by human observers of the system with limited intelligence or computational potency and thus remain VUCA for the human mind.

Figure 28 now integrates the obtained insights into Figure 25 where type I & III systems are bordering to organized simplicity, type II systems bordering to unorganized complexity and type 4 systems represent most modern industrial systems in the realm of organized complexity, exemplified through CPS for the context of Industry 4.0 and a VUCA business environment.

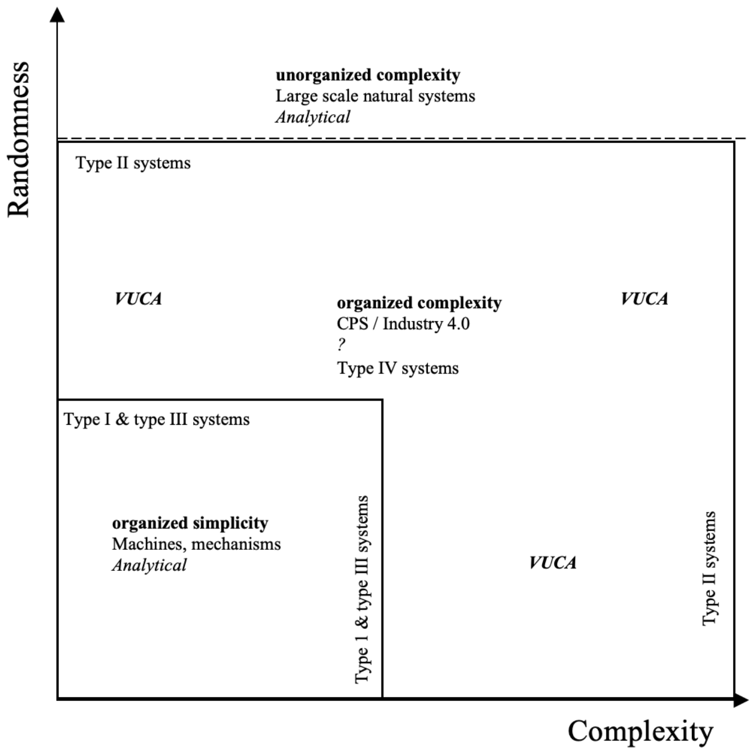



*Figure 28: CPS in the context of organized complexity*

Based on Figure 28 this now allows to introduce the questions how strategic complexity management can potentially alleviate the introduced problem deriving from the assumptions of the *Principle of Computational Equivalence*, as it remains often unclear which methods are applicable to the management of the complexity of type 4 systems and organized complexity in general. (Jackson, 2019, Collier, 2010) According to Wilson (2014) one option to approach a system of organized complexity is the effective deployment of a metaphor for analysis and theory building, which is well-reflected in SMTTs like SWOT matrix or even more literally in the BCG matrix, in the form of dogs, cows, stars and question marks.

In this context the aspects defined in the research of Kirchhoff et al. (2003), Jackson (2019) and Collier (2010) are now particularly interesting when regarded in the context of corporate strategy and decision-making for complex systems to establish an argument why strategic complexity management can contribute to solve the described problem at hand.

Therefore, the next section now further elaborates on complexity management and corporate strategy.

### 6.4.2 Complexity management and corporate strategy

Eisenhardt & Piezunka (2011) and Hessami (2020) emphasize that strategy in the complexity perspective comes from the improvisational actions of managers within the guidelines of simple heuristic rules, leading to a *strategy of simple rules*, sometimes defined as "simplexity". Complexity theory thus proposes simple rules to guide autonomously acting managers, decision-makers, accordingly to a pre-defined schema that aims to act on complexity with simplicity, thus leading to the idea of simplexity as the central theme of complexity management. (Hessami, 2020)

In this context, Gorzen-Mitka & Okreglicka (2015) define the main strategic goal of complexity management on an abstract level as minimized value-destroying complexity and efficiently controlled value-adding complexity. They furthermore postulate that complexity management is determined by the search for new management strategies and methods that fit in with the reality of the decision-making practitioner facing complexity.

It is concluded by Eisenhardt & Piezunka (2011) that complexity theory adds a rich understanding of corporate strategy to the organization theory and strategy through a holistic and systemic focus of complexity theory as an essential lens to better understand causalities in corporations in order to better manage problems of organized complexity and type 4 systems.

The previous statements underline the importance of the requirements for innovative strategic thinking in a complex system environment of organized complexity and type 4 systems.

Based on the research by Paparone et al. (2008) and Mittal et al. (2018) these are now defined as the following:

- **Relationship building:** Whereas traditional bureaucratic approaches have treated organizations as collections of roles and focused on role management, complexity management promotes and assist in building longer-term relationships that enhance operational effectiveness.
- **Improvising:** Improvisation is a necessary condition in a VUCA environment, and the organization must have the capacity to respond to unanticipated circumstances.
- **Loose coupling:** Micro-management and over-supervision can lead to suboptimal performance. Instead of one-stop solutions, decision-making in VUCA environments benefits from parallel searches for diverse solutions and their adaptive consideration as decision factors.

- **Sense-making:** Deriving as a shared understanding of the organizational purpose and one's place therein, members can begin to create shared meaning which, in turn, can serve as a normative and heuristic decision- guide.
- **Learning:** Complexity management is based on the concept of the learning organization that create opportunities for knowledge sharing and norm creation.
- **Emergent thinking:** Under VUCA conditions, forecasting and formal planning is less than useful. Instead, thinking about the future in new ways is called for.

In this light, Hummelbrunner & Jones (2013) define three key-barriers to effective complexity management:

- **Adaptation:** Decision-makers should depart from command-and-control management traditions and be more open to adaptive approaches that are responsive to contextual changes and lessons learned from implementation.
- **Approaches:** Integrating new approaches procedures and more adaptive complexity management tools.
- **New rules:** Current practice and rules with respect to analytical performance / results-based management should be revised to better make use of unexpected effects in complex situations.

This shows that effective strategic complexity management models open a new perspective of looking at decision-making in organizations and that complexity can be managed via simple but unique strategies underlining the importance and relevancy of SMTTs for complexity management.

This is in line with Boulton et al. (2015), who describe their philosophy of strategic complexity management as interventionistic *pragmatism*, meaning that knowledge about the behavior of complex systems can only ever be local and contextual and possible action is limited to trying to find out "what works" based on trial and error and reflection, again underlining the importance and potency of SMTTs for complexity management to achieve the practical integration of strategic complexity management.

Based on these insights, the next section now introduces and describes the concept of strategic complexity management for industrial systems.

## 6.5 Strategic complexity management for industrial systems

In the light of the results of the previous sections and based on the works of Alkan et al. (2018), Furnari at. al (2021) and Morcov et al. (2021) the now proposed underlying logic of strategic complexity management now summarizes the core statements made up to this point. The underlying logic is illustrated in the following Figure 29.

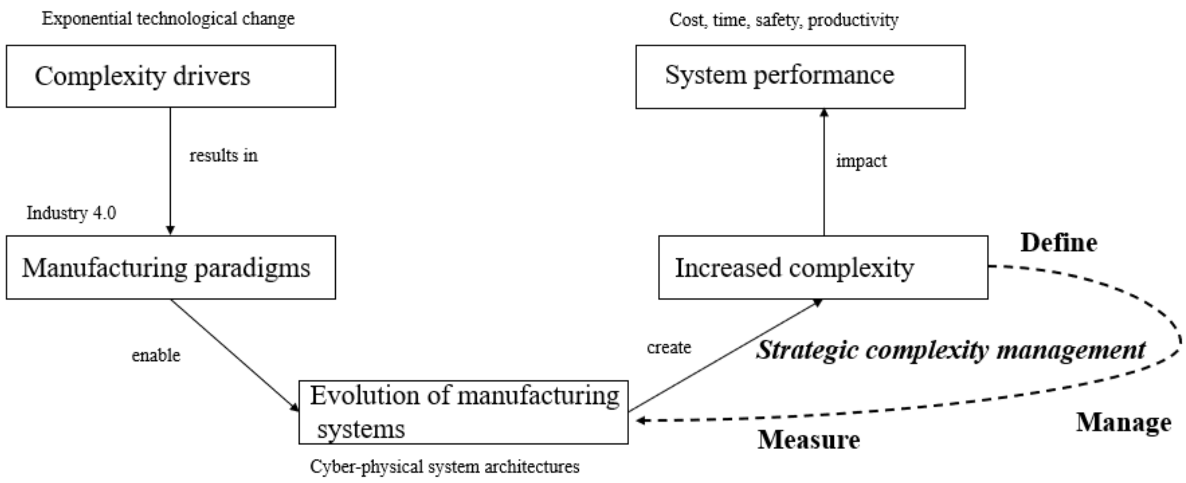



*Figure 29: Strategic complexity management for industrial systems*

The provided figure summarizes the existence and evolution of complexity in the manufacturing industry along with the identified and discussed cause-effect relationships based on the IKTF. It shows that the logic of strategic complexity management starts at the macro level of complexity drivers in the form of exponential technological change.

The complexity drivers result in new manufacturing paradigms, embodied by Industry 4.0. These new manufacturing paradigms now enable the evolution of existing manufacturing systems, in the context of Industry 4.0 the evolution from traditional embedded systems to cyber-physical systems.

These systems create increased complexity which then impact the performance of the respective system for example in terms of cost, time, safety, or productivity parameters. To enhance positive impacts and to mitigate negative impacts of the generated complexity the strategic complexity management cycle of *Define, Manage and Measure* is then applied to create a feedback loop to the evolution of manufacturing systems.

Based on this, the next section now provides more detail on the strategic complexity management cycle.

### 6.5.1 The strategic complexity management cycle

Based on the work of Alkan et al. (2018), Furnari at. al (2020) and Morcov et al. (2021) the strategic complexity management cycle as shown in Figure 30 can be illustrated as the following.

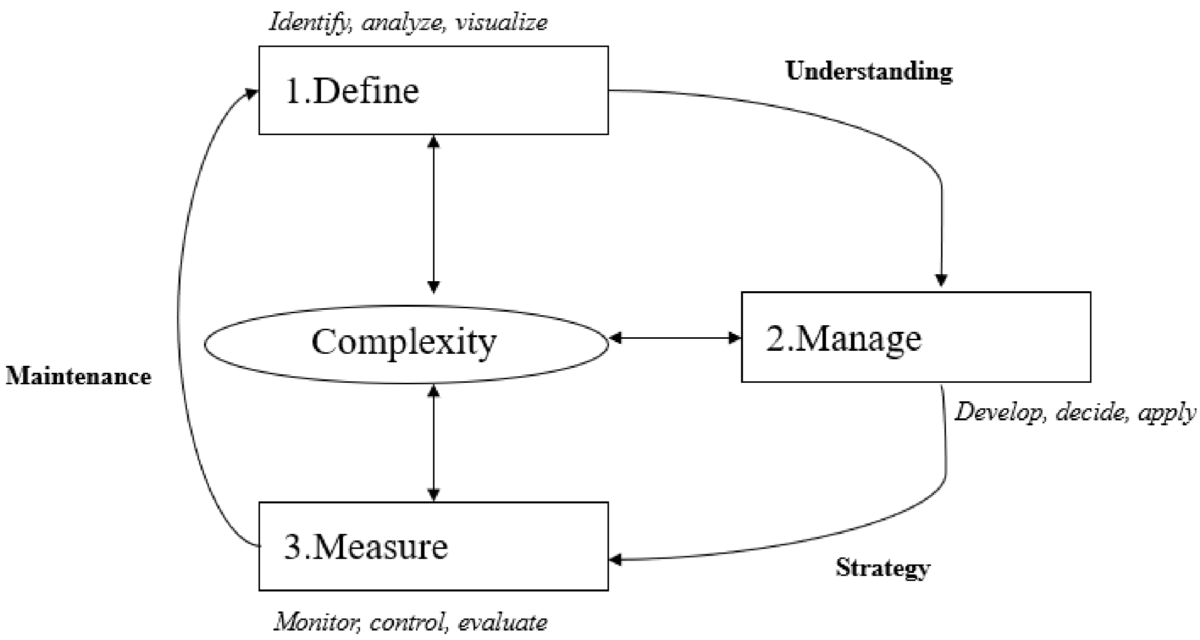



*Figure 30: The strategic complexity management cycle*

As shown, the strategic complexity management cycle now consists out of three rudimentary steps, define, manage, and measure, which center around and are in a feedback loop with the system´s perceived complexity.

The next sections now further define the illustrated steps.

### 6.5.2 Define

The step of "Define" can now be defined as the following:

- **Identify:** Identify sources of complexity in the analysed system.
- **Analyse:** Evaluate the impact of the identified sources of complexity.
- **Visualize:** Visualize the results in a comprehensive manner.

Consequently, the main goal of this step is to better understand the complexity of the analysed system.

### 6.5.3 Manage

The step of “Manage” can now be defined as the following:

- **Develop:** Develop strategic directions to improve the complexity situation.
- **Decide:** Decide on one strategic direction.
- **Apply:** Apply the strategic direction on the system.

Therefore, the main goal of this step is to develop a strategy to deal with the complexity of the analysed system.

### 6.5.4 Measure

The step of “M**easure**” can now be defined as the following:

- **Monitor:** Track the systems behaviour.
- **Control:** Regulate the system according to its target function with optimization approaches, for example six-sigma or simplex models.
- **Evaluate:** Evaluate the efficiency and efficacy of the regulation. Restart the cycle with new knowledge, when necessary.

To conclude, the main goal of this step is to **achieve maintenance** of the complexity of the analysed system.

After explaining the strategic complexity management cycle in more detail, the section to follow elaborates on why heuristics are highly relevant to enable strategic complexity management.

## 6.6 Why heuristics matter for strategic complexity management

As already indicated by the previous chapters, SMTTs are based on the heuristics category of methods to assess manufacturing complexity and appear to be generally applicable by complexity management approaches in the context of solving problems of organized complexity.

To underline the importance and relevance of heuristics as a foundational paradigm for the development of SMTTs for complex industrial systems, this section now further elaborates on this topic and on how heuristics help to solve complex decision-making problems.

The origin of the term heuristic is the Greek word for "serving to find out or discover." Heuristics are strategies to solve problems that logic and probability theory cannot handle. Heuristics can thus be highly functional in uncertain environments. (Artinger et al., 2014)

According to Gigerenzer & Gaissmaier (2011), decisions can generally be made in three different ways.

The human mind either applies logics, statistics, or heuristics. These tools often are not treated as equals, with rules of logic and statistics having been linked to rational reasoning and heuristics linked to error-prone intuitions or even irrationality.

The bottom line of this train of thought often is that people rely on heuristics, but they would be better off in terms of accuracy if they did not.

These arguments are often based on the perception of fully informed, completely rational agents positioned in so-called small-world situations, worlds which are predictable and without surprises.

In so-called large worlds parts of the information are unknown, making optimal reasoning impossible. (Binnmore, 2009)

Gigerenzer & Gaissmaier (2011) further state that for many situations simple heuristics were more accurate than statistical methods. The study of heuristics is furthermore based on two central questions which are to be answered if heuristics shall be applied. (Gigerenzer & Gaissmaier. 2011)

- **Prescription:** When should people rely on a given heuristic rather than a complex strategy to make more accurate judgments?
- **Description:** Which heuristics do people use in which situations?

Based on the statements made the following definition of heuristics shall be applied for this thesis, based on Gigerenzer & Gaissmaier (2011):

*“(...) heuristic is a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods.”*

It is important to mention that heuristics in this context are to be regarded as a subset of strategies, in which there is no strict dichotomy between heuristic and non-heuristic, as strategies can ignore a more or a less amount of information.

Consequently, it may be possible that Bayesian approaches, AI or NN can also fall in the category of heuristics if they are heuristically applied, in sense that one could use these approaches more intensively or alternatively try to test smarter when faced with complex system which exhibit emergent behavior. (Haugen & Ghaderi, 2021)

As a next step, the following sub-section now describes how heuristics work.

### 6.6.1 How heuristics work

Heuristics rely on limited information and employ simple computational mechanisms. As mentioned, they have often been regarded as second-best solutions compared with optimization models, like Six-Sigma, based on the assumption of an accuracy–effort trade-off, meaning that lower effort yields lower accuracy.

As information search is usually costly, optimization under information and resource constraints might still ignore some of the potentially available information and be less effective and efficient due to information search costs.

This nevertheless still implies that, in theory, more information is always better, apart from its costs.

### 6.6.2 The less-is more effect of heuristics

It can be indicated that there are several conditions under which there exists a *less-is more effect*, where more information and computation in optimization models beyond a certain point can in fact decrease performance, even if there are no costs associated with information search (Gigerenzer & Gaissmaier, 2011, Gigerenzer & Brighton, 2009). Optimization shall be defined as a class of problems that seek to maximize or minimize a mathematical function of several variables and are subject to certain constraints with the goal to maximize or minimize. (Gill et.al, 2019)

This allows to infer that the empirical observation of the *less-is more effect* thus at least partially may disagree with the *Principle of Computational Equivalence* by Wolfram (2002) as defined in Chapter 6.4.1.

The explanation why the *less-is more effect* is the case is based on the relation between effort and accuracy, which is U-shaped: Too little or too much effort is detrimental.

For example, it might not be best for a firm to respond to new information about changes in a market immediately. Instead, a certain degree of rigidity can provide a competitive edge. (Bingham et al., 2007)

Wübben and von Wangenheim (2008) compared in their studies the so-called optimization models (for example Bayesian analysis or Six-Sigma and thus representative for traditional scientific analysis and AI and NN representative for more recent optimization advances) with simple heuristic approaches and found that the heuristic consistently performed at least as well as or better than the optimization models across several different industries.

Figure 31 now illustrates the less-is more effect of heuristics.

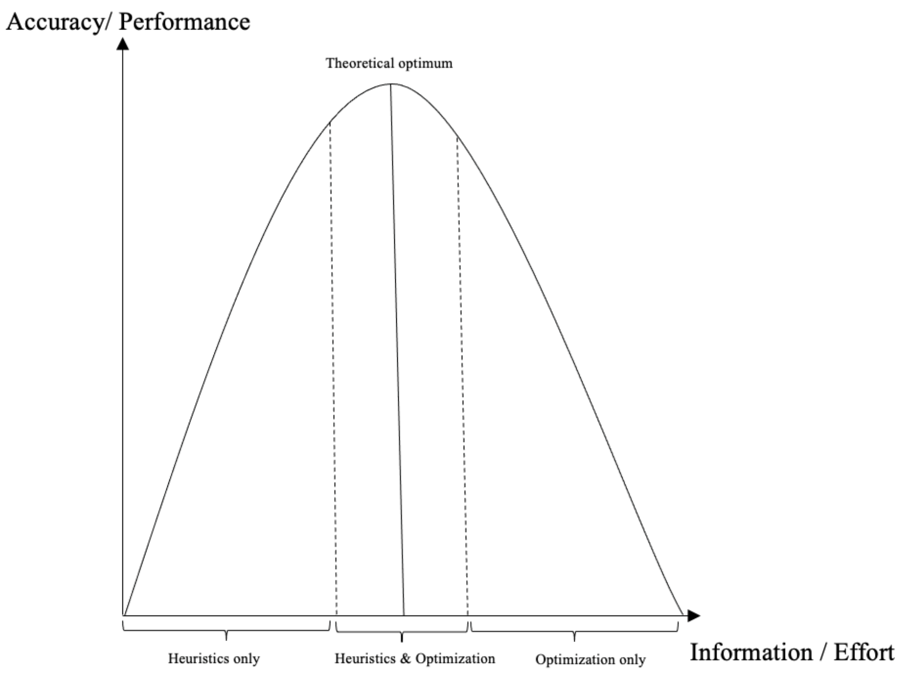



*Figure 31: Heuristics vs. optimization*

Figure 31 shows that the efficiency of a decision-making model can be characterized by two dimensions:

- **Accuracy / Performance:** How well the decision-making model achieves a system´s target function

- **Information / Effort:** How much information and thus effort is required to achieve the relative level of accuracy / performance.

It is now furthermore shown that the efficiency of a decision-model is characterized by a U-shaped function with three paradigms:

- **Heuristics only:** Only heuristic decision models can be applied
- **Heuristics & Optimization:** Both heuristic and optimization decision-making models can be applied
- **Optimization only:** Only optimization decision-making models can be applied

In this light it is now shown that heuristics require less effort to be generally applied and to achieve a given performance until reaching maximum performance at the theoretical performance optimum point.

Optimization in comparison requires more effort and information to be generally applied and has only a short interval where effort and performance are in a proportionate relationship until the performance deteriorates with significant information and effort, leading to a more-is less effect of optimization models.

It is consequently implied that relying on heuristics can be rational in the sense that costs of effort are higher than the gain in accuracy, while the decision is also impacted by the limited cognitive capacities of the decision-maker. (Gigerenzer & Gaissmaier, 2011)

Based on these thoughts Artinger et al. (2014) and Hallo el. al (2020) furthermore underline the statements made by proposing that heuristics are to be regarded as simple decision strategies that function well with relatively little information in a complex environment like VUCA and often lead to higher outcomes and profit.

This circumstance is also supported by the research of Islam et al. (2014) who show in their study that medical experts manage complexity using heuristics to develop efficient and fast decision strategies to simplify complex decision tasks while focusing on only the most relevant information.

This stresses the importance of management practitioners being aware of the different basic decision strategies that have been identified as successful tools in an uncertain, complex environment like a VUCA manufacturing system and organized complexity in general.

To support this argumentation the next section now introduces the so-called bias-variance dilemma as a more in-depth explanation for the less-is more effect of heuristics.

### 6.6.3 The bias-variance dilemma

A general statistical explanation for the less-is more effect of heuristics is the so-called bias-variance dilemma. Often the term bias refers to the deviation of average judgment from a rational decision-making norm. This contrasts with the statistical literature that investigates the role of bias when a decision maker operates in an uncertain world where an inference needs to be drawn from limited data or is faced with problems of high complexity, such as it is often the case in managerial decision making in a VUCA world. (Artinger et al., 2015) The bias-variance dilemma is now defined by Equation (1).

$$(1)\ Total\ error = (bias)2 + variance + noise$$

Equation (1) summarizes a decision strategy's sources of error when making predictions. The true underlying function is not known but must be estimated from a sample. The components of Equation (1) can be defined as the following:

- **Bias**: Refers to the deviation of the mean across samples from the true underlying mean.
- **Variance:** Reflects the degree of systematic variation of the individual sample means.
- **Noise:** Refers to unsystematic variation of the data.

As already established, a central element of any heuristic is that it is simple, meaning that it estimates few or even no parameters and ignores the remaining information.

Through this, it is possible to minimize variance owing to estimation error. Thus, its error in prediction comes mainly from bias and less so from variance. (Artinger et al., 2015)

This also provides an explanation for the lacking efficiency of optimization models in complex environments, which by nature rely on the underlying sample of data to be accurate with as less variance and noise as possible.

In this light it appears reasonable to assume that variance and noise are high in a VUCA environment, providing further indications why optimization models might be difficult to implement for decision-makers in such environments.

As a next step, the following section now describes how heuristics can be applied to establish a SMTT for strategic complexity management.

### 6.6.4 Heuristics as the basis for the development of SMTTs for strategic complexity management

Heuristics describe thus a shift in thinking that can be harmonized with the assumptions of complexity theory, complexity management and the requirements of strategic complexity management and SMTTs for industrial systems.

As already established, managers of complex industrial systems must make increasingly difficult decisions in an uncertain environment with limited information and time constraints often owing to competitive pressure while they might use complex models for well-understood, simple environment in organized simplicity to increase competitive advantage.

In summary, in a complex environment with limited information at hand, there is strong evidence in the reviewed and discussed literature that a heuristic approach often can be beneficial over a pure optimization approach due to the less-is more effect of heuristics and the more-is less characteristics of optimization models, indicating the high potential of SMTTs for strategic complexity management.

In this context strategic complexity management for complex industrial systems positioned in organized complexity shall be defined as directly linked to heuristics and the application of SMTTs for the purpose of this study.

Figure 32 now summarizes the statements made in the context of organized complexity.

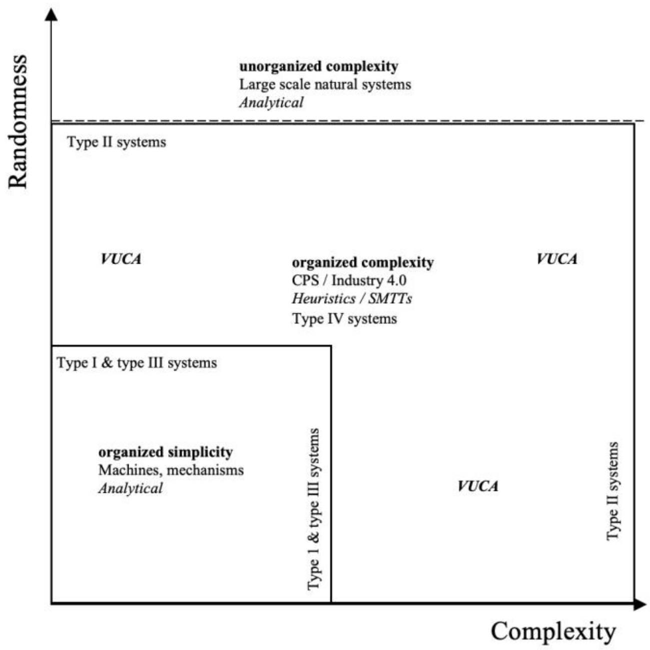



*Figure 32: Heuristics in the context of organized complexity*

Figure 32 shows, that organized complexity and, accordingly, type 4 systems like CPS, are to be regarded as represented in the line of argument of this thesis as the realm of heuristics in terms of analytic method of choice and thus is assumed to be the primary applicative zone of SMTTs for strategic complexity management of industrial systems in a VUCA business environment. (Wade & Heydari, 2014)

Based on these statements the next section now introduces and discusses four prominent complexity management frameworks to illustrate how heuristics are translated into applicable management frameworks for industry practitioners to better deal with complex decision-making environments and type 4 systems in general.

## 6.7 Complexity management frameworks

As a next step, this section now introduces, discusses, and compares four prominent complexity management frameworks applicable for industrial systems:

- Cynefin Framework
- Stacey Agreement and Certainty Matrix
- Schuck´s Knowledge-Control Matrix
- MITRE Enterprise Systems Engineering Profiler

Consequently, the Cynefin Framework is described and discussed in the next subsection

### 6.7.1 Cynefin Framework

The Cynefin framework is a phenomenological framework, meaning that it is about how people perceive and make sense of situations to make decisions. It is consequently focused on solving symptoms of complexity related to human perception.

Cynefin has two large domains: Order and Unorder, each containing two smaller domains: Simple and Complicated in the Ordered domain, and Complex and Chaotic in the Unordered domain. (Gray, 2017, Wade & Heydari, 2014)

The Cynefin framework sees relevant application in practice, for example by the research offices of the European Union. (Snowden & Rancati, 2021)

Figure 33 now illustrates the Cynefin framework.


*Figure 33: Cynefin framework (Gray, 2017)*

Based on Gray (2017) the 5 Cynefin domains can be summarized as the following:

- **Simple:** Simple is the domain of best practices, where problems are well understood, and a solution requires minimal expertise. Many issues addressed by help desks fall into this category. They are handled via pre-written scripts. The correct approach is to sense the situation, categorize it into a known pattern, and apply a well-known, and potentially scripted, solution.
- **Complicated:** Complicated is the domain of good practices, where you are likely to know the questions that need to be answered and how to obtain the answers. Assessing the situation requires expert knowledge to determine the appropriate course of action. The correct approach is to sense the problem and apply expert knowledge to assess the situation and determine a course of action.
- **Complex:** Complex is the domain of emergent solutions, where there are unknown unknowns, and the final solution is only apparent once discovered. The correct approach is to develop and experiment to gather more knowledge to determine the next steps, with the goal of moving your problem into the ‘Complicated’ domain.
- **Chaotic:** Chaotic is the domain of novel solutions where the immediate priority is containment. The correct approach is to triage, once you have a measure of control, assess the situation and determine next steps, with the goal of moving your problem into another domain.

- **Disorder:** Disorder is the space in the middle where you don’t know where you are and the priority one is to move you to a known domain. The correct approach is to gather more information on what you know or identify what you don’t know to be able to move to a more defined domain.

It is shown that the tool is based on the idea that decision-makers learn to better “sense” the characteristics of the decision environment they are situated in and provides help to change and adapt to this context.

Consequently, the Cynefin Framework can be regarded as generalist “sensemaking” tool which focuses on how the decision-maker as a leader and how this person perceives a situation.

In a best-case scenario applying the Cynefin framework can help decision-makers sense and better perceive which context they are in so that they can not only make better decisions but also avoid the problems through applying the right type of leadership practice. (Gray, 2017)

It is important to state that the Cynefin framework does not provide clear directions in the form of strategies how a decision-maker might implement the knowledge generated through the framework.

The next section now introduces and discusses the Stacey Agreement and Certainty Matrix.

### 6.7.2 Stacey Agreement and Certainty Matrix

In the Stacey Agreement and Certainty Matrix (Stacy Matrix) complexity is analyzed on two dimensions, the degree of certainty and the level of agreement and is illustrated in Figure 34.

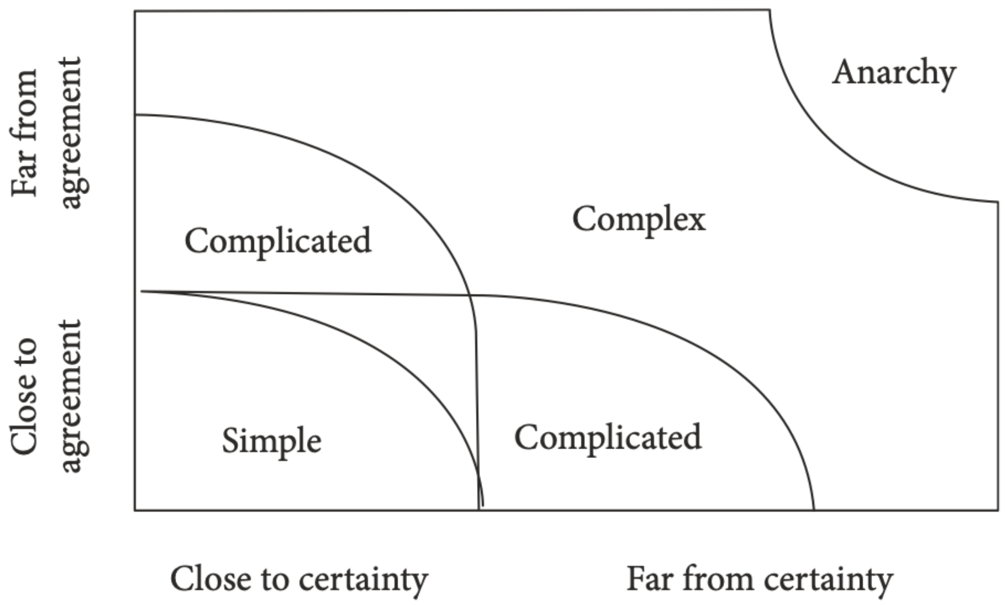



*Figure 34: Stacey Agreement and Certainty Matrix (Cristobal et al., 2018)*

Based on Cristobal et al. (2018), these dimensions can be described as the following:

- **Close to agreement, close to certainty:** Traditional management techniques work well, and the goal is to identify the right process to maximize efficiency and effectives.
- **Far from agreement, close to certainty:** Coalitions, compromise, and negotiation are used to solve this type of situations.
- **Close to agreement, far from certainty:** Traditional management techniques may not work, and leadership approaches must be used to solve this type of situations.
- **Far from agreement far from certainty:** Anarchy with a high level of uncertainty and where traditional management techniques will not work.

The Stacey Matrix can be regarded as tool that allows decision-makers to, like the Cynefin Framework, make sense of an array of decisions in a decision-making environment. Also, the Stacey Matrix is based on "political" decision-making aspects like communicating and negotiation with other system stakeholders in order to clarify why a given particular leadership approach might be appropriate to solve the complex situation. Nevertheless, the Stacey Matrix does not provide any precise strategic guidance how this leadership approach might manifest. Consequently, the Stacey Matrix must be regarded as a generalist “sensemaking” tool as well.

The next section now introduces and discusses Schuck´s Knowledge -Control Matrix.

### 6.7.3 Schuck´s Knowledge – Control Matrix

Schuck (2019) introduces the Knowledge – Control Matrix (Schuck Matrix) which is based on the two-dimensional knowledge matrix that is related to the practice of risk analysis, control, and management science.

The Knowledge-Control Matrix follows the pattern shown in Figure 35.

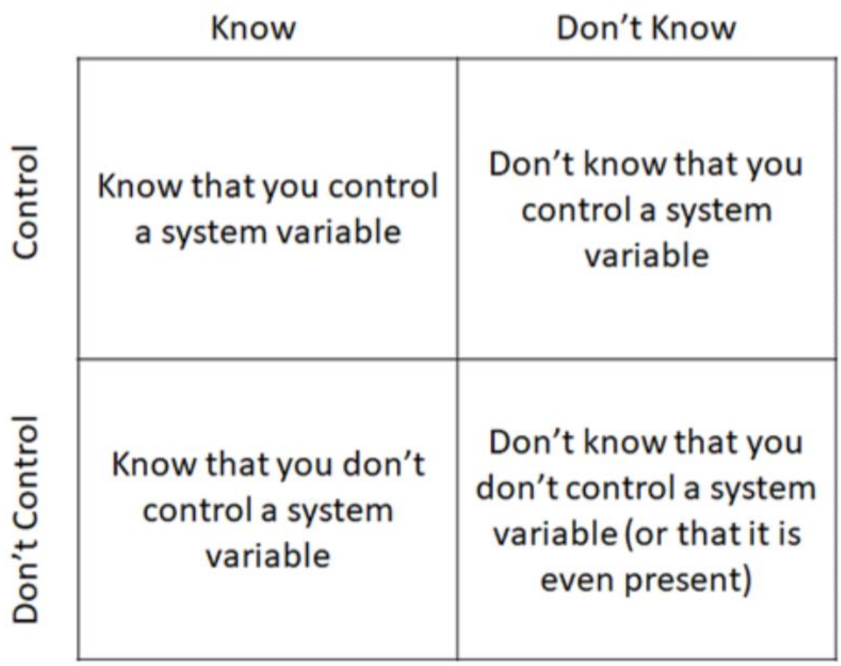



*Figure 35: Schuck´s Knowledge - Control Matrix (Schuck, 2019)*

According to Schuck (2019) the Schuck matrix is a way of generating knowledge about an industrial system or engineering event via four quadrants that include “known knowns”, “known unknowns”, “unknown knowns”, and “unknown unknowns”. A general systems assumption will default to quadrants 1 and 3 in Figure X. It is assumed to be much more difficult to understand and quantify the “Don’t Know” column (quadrants 2 and 4), at least during the early design stage before system prototypes are built and tested. Quadrants 2 and 4 is where emergence is likely to occur. As already stated, emergent properties are very often destabilizing in human engineered complex systems unless accounted for in design and execution.

The Schuck Matrix aims to allow decision-makers to better understand a given system in terms of controllability of the system.

Consequently, the Schuck Matrix is to be regarded as a sensemaking tool but differs from the Cynefin Framework and the Stacey Matrix as it is primarily concerned with generating knowledge about an industrial system in terms of control and is less focused on how the decision-maker perceives a situation from a personal or political point of view. Also, the Schuck Matrix does not provide any proposals how a situation might be approached strategically by the decision-maker after having generated knowledge.

The next section now introduces and discusses MITRE Enterprise Systems Engineering Profiler.

### 6.7.4 MITRE Enterprise Systems Engineering Profiler

According to Stevens (2008) and Gorod et al. (2014) it is designed to be a complexity self-assessment tool that can help the systems engineer and program manager understand the nature and context of the program/project of interest. It is also intended as the basis of a situational model that can help in selecting and adapting the processes, tools, and techniques most applicable to the problem and its context.

The MITRE Enterprise Systems Engineering Profiler is now shown in Figure 36.

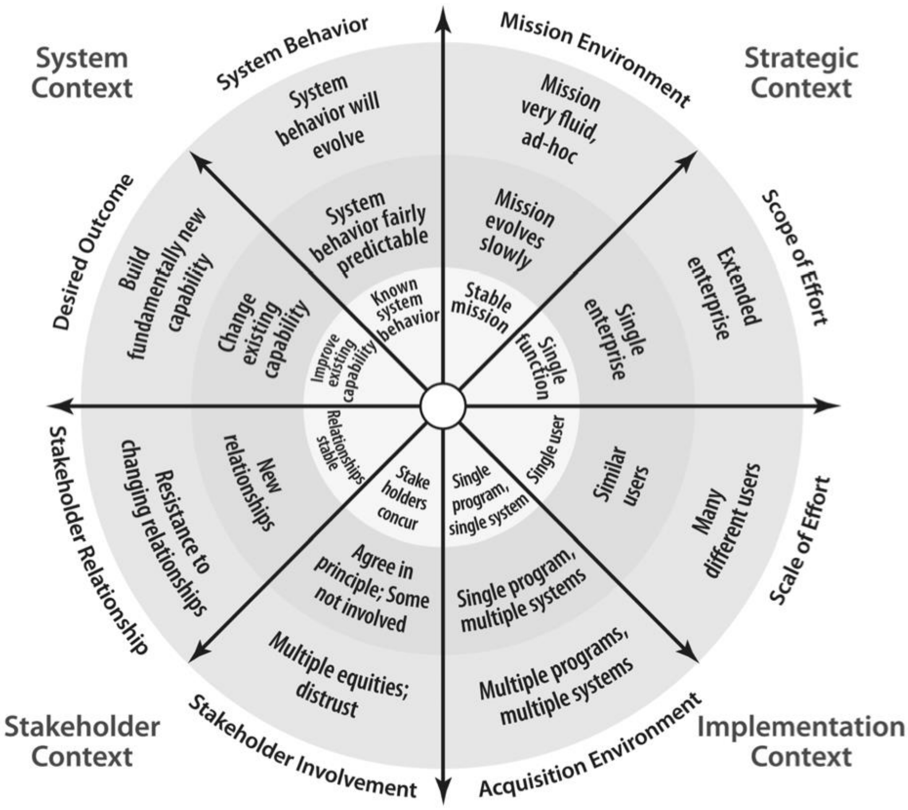



*Figure 36: MITRE Enterprise Systems Engineering Profiler (Stevens, 2008)*

As shown in Figure 36 the MITRE Enterprise Systems Engineering Profiler is based on a four-quadrant matrix format that is enhanced by three rings. The quadrants describe the different dimensions of the broader context in which the system, system-of-systems, or enterprise-wide system are developed, will operate in, or will evolve to. The three concentric rings reflect increasing levels of complexity and uncertainty.

Based on Stevens (2008), the dimensions can be described as the following:

- **Strategic context:** Dimensions related to the stability of the task environment and the scope of the intended effort. Requirements for systems that are to operate in a stable environment are expected to change more slowly than those for systems that will operate in environments that are themselves changing.
- **Implementation context:** This context can range, at its simplest, from a single program that is established to implement a single system to the obviously more complicated activities associated with multiple programs organized to implement multiple, though operationally interrelated systems.
- **Stakeholder context:** The extent to which stakeholders agree with the goals and objectives of the effort and the extent to which stakeholder relationships are changing.
- **Systems context:** The expected outcome of the effort as well as on the behavior of the system itself. The expected outcome can range from small improvements to an existing capability to the development of a fundamentally new capability, often by leveraging emerging technologies.

In this context the rings now reflect increasing complexity, uncertainty, and variability with complexity increasing from the innermost ring to the outermost ring.

The MITRE Enterprise Systems Engineering Profiler allows decision-makers to better understand the complexity of a system or system of systems in terms of a wide range of characteristics and in the context in which it is being engineered, developed, and acquired and in which the system will operate. To achieve this, the framework focuses on how decision-makers perceive the system and aims to improve intra and inter team communication.

Also, the MITRE Enterprise Systems Engineering Profiler itself does not provide any structured proposals how a situation might be approached strategically by the decision-maker after having generated knowledge. Strategies have thus to be individually defined based on the individual situation of application. (Stevens, 2008)

The next section now provides a comparison and discussion of the presented frameworks.

### 6.7.5 Comparison of complexity management frameworks

Table 8 now compares the presented frameworks with each other and with an SMTT in the form of the SWOT analysis.

*Table 8: Comparison of complexity management frameworks*

| Framework | Method | Format | Purpose | Focus | Strategic |
|---|---|---|---|---|---|
| Cynefin | Heuristics | Matrix | Sensemaking | Complexity | no |
| Stacey | Heuristics | Matrix | Sensemaking | Complexity | no |
| Schuck | Heuristics | Matrix | Sensemaking | Control / Complexity | no |
| MITRE | Heuristics | Matrix | Sensemaking | Complexity | no |
| *SWOT (SMTT)* | Heuristics | Matrix | Strategic external and internal analysis of system | Business | yes |

Based on Table 8, the introduced complexity management frameworks allow to draw several conclusions concerning the underlying generalities of prominent complexity management frameworks. These are now shown in Table 9.

*Table 9: Complexity management framework generalities*

| Generality | Description |
|---|---|
| Format | All frameworks are based on a matrix format. |
| Method | All frameworks utilize simple categorization functionalities / heuristics. |
| Purpose | All presented complexity management frameworks are general “sensemaking” tools. |
| Focus | Three complexity management frameworks (Cynefin, MITRE and Stacey Matrix) are focused on how a decision-maker, or a team perceives a situation, the Schuck Matrix has a focus on a given industrial system. |
| Lack of strategic functionality | No complexity management framework can be regarded as of inherently strategic when compared to the functionality of a SMTT dedicated to business strategy, exemplified by SWOT. |

Overall, it can be stated that the presented complexity management frameworks have distinct unifying characteristics in terms of format, method, purpose and, partially, focus.

It is made evident that even though there are similarities to a SMTT in term of basic format, method and functionality, contemporary complexity management frameworks differ in the core aspect that they are of a primarily phenomenological nature without any precise strategic and system component integrated like it can be found in an inherently strategic SMTT like SWOT.

The next section now integrates and interprets these results in the strategic complexity management cycle.

## 6.8 The strategy gap of current complexity management frameworks

If interpreted in the context of the strategic complexity management cycle the following Figure results.

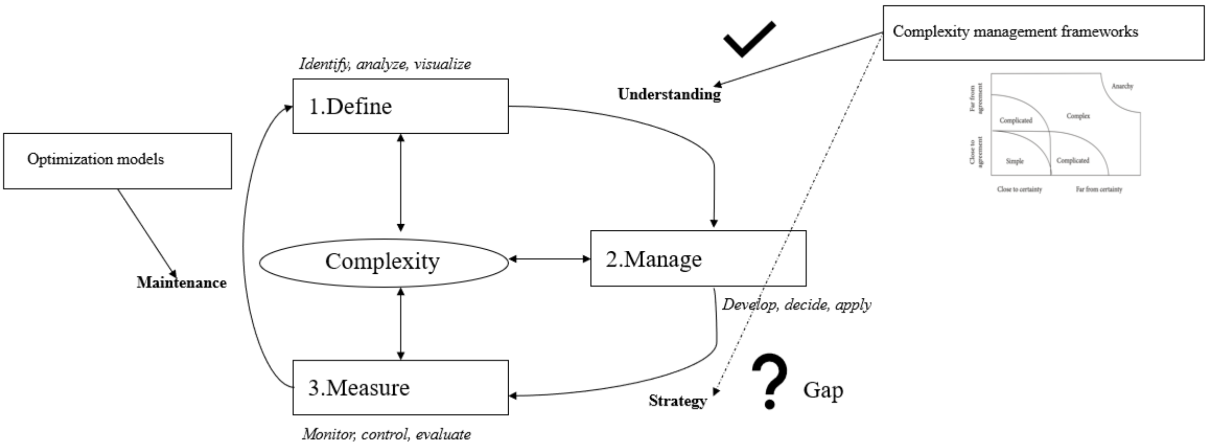



*Figure 37: The strategy gap of current complexity management frameworks*

Figure 37 shows that complexity management frameworks appear generally applicable to the first step of the cycle “Define – Understanding complexity” as they in principle allow to identify, analyze, and often visualize complexity.

Optimization models, like Six Sigma, are now attributed to third step “Measure – Maintaining the system” ,if applicable, due to reasons already described and discussed and are not to be regarded as an essential topic for this thesis.

It is now apparent that there is a definitive gap in the strategic complexity management cycle, since the second step “Manage- Developing and applying strategy” is not covered by the complexity management frameworks presented and discussed but would be covered in a more general business context by a SMTT like SWOT.

The identified gap is in line with the propositions of Törgren & Grogan (2018) in the context of complex CPS who state that there is a strong need for new models to engineer and manage industrial CPS.

To practically underline the statements made, Kasser´s (2018) comprehensive collection of one hundred heuristic complexity management tools does primarily contain sense-making or creative tools and does not contain explicitly strategic complexity management tools.

Figure 38 now summarizes the position and methodological approach of strategic management in the light of the literature reviewed.

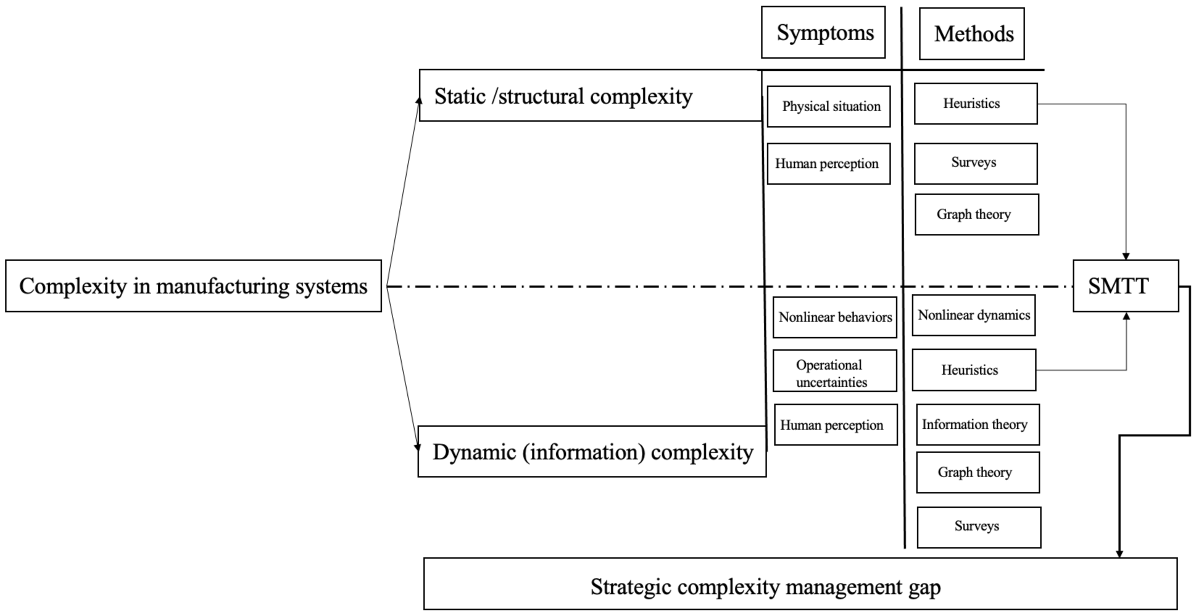



*Figure 38: SMTT methodology in the context of complex industrial systems*

As a conclusion to the previous chapters Figure 38 now illustrates that SMTTs are a theoretically applicable heuristics-based assessment method for both complexity dimensions in manufacturing systems to address the identified gap.

This described gap shall be defined for this thesis as the *strategic complexity management gap* and provides a coherent explanation for the motivation of the research question and core aim of this study as the central conclusion to this section.

Consequently, the research aim, objectives and research questions of this thesis are introduced in the next section.

# 7 Research aim, research objectives and research questions

The research aim, research objectives and the research questions of the thesis are now introduced.

## 7.1 Research aim

In accordance with the identified *strategic complexity management gap* the research aim of this thesis shall be defined as the following:

*Development and practical application of a strategic complexity management framework for complex industrial systems.*

Based on the research aim, the research objectives can now be introduced.

## 7.2 Research objectives

To achieve the defined aim this thesis now has the goal to develop and present a novel strategic complexity management tool (SCM). This goal is achieved through reaching the following thesis objectives:

- ***Objective 1 (O1):*** **Development of a multi-dimensional definition for industrial system complexity**
  *Description:* Through review, synthesis, and analysis of the current body of research a working definition of complexity is developed in the form of a set of hypotheses concerning the nature of complexity and its implications for decision-makers in industrial systems.
- ***Objective 2 (O2):*** **Development of a complexity model for industrial systems**
  *Description:* Based on (O1), a modelling approach for exploratory analysis is developed to theoretically model and visualize the developed conception of complexity for industrial systems.
- ***Objective 3 (O3):*** **Development of a strategic complexity management framework**
  *Description:* (O1) and (O2) are applied to develop a strategic management tool for practical industry application in the form of the Strategic Complexity Management framework (SCM).
- ***Objective 4 (O4):*** **Application of the SCM on real-world cases in the European manufacturing industry**

*Description:* Based on (O3): The SCM is applied on real-world industry case studies with a document review and analysis methodology.

Based on the introduced objectives of the thesis the corresponding main research question can now be formulated.

## 7.3 Research question

In the light of O1-O4 the main research question (MR) for this thesis can now be defined as the following:

***Main research question (MRQ):*** **Can the complexity of industrial manufacturing systems be managed via the strategic complexity management framework (SCM)?**

Based on the MRQ, the resulting sub-research questions (SRQ) can be introduced.

### 7.3.1 Sub-research questions

The following sub-research questions (SRQ 1-SRQ4) of the MRQ result in accordance with the defined research objectives (O1 – O4):

- ***Sub-research question 1 (SRQ1; O1):*** **How can the nature of complexity in industrial systems and its impact on decision-makers be defined?**
- ***Sub-research question 2 (SRQ2; O2):*** **How can industrial system complexity be theoretically modelled?**
- ***Sub-research question 3 (SRQ3; O3):*** **How can the strategic complexity management framework (SCM) for industrial systems be coherently established?**
- ***Sub-research question 4 (SRQ4; O4):*** **Can the strategic complexity management framework (SCM) be applied on real-world industrial systems?**

The MRQ and SRQ1-SRQ4 are providing a novel contribution to industry decision-makers so that they can obtain methods and tools of strategic planning addressing the management of complex industrial systems, like CPS system architectures.

The study achieves this by the development and practical application and evaluation of a strategic management framework SMTT based on a solid theoretical foundation of hypotheses and a dedicated model.

On this basis the addressed research gap is described in more detail in the next section.

## 7.4 Addressed research gap

As shown in the previous chapters, there is an expressed need to develop complexity management frameworks that integrate different individual, subjective measures of identifying and dealing with complexity into a synergetic strategic framework.

This then allows to effectively address the already defined *strategic complexity management gap*.

In correspondence to this notion and as reflected in MRQ, SRQ1- SRQ4 and O1-O4 the core aim of the proposed study is to develop a strategic complexity management SMTT.

Such an SMTT dedicated for the strategic management of complex industrial systems can contribute to mitigate the identified gap and to develop novel strategic complexity management strategies and methods that fit in with the individual reality of the decision-making practitioner.

This is achieved by integrating different complexity dimensions in a holistic, synergetic way, while being based on a coherent in-depth theoretical foundation, namely a dedicated model of complexity.

This model is in turn based on the development of a specific and dedicated multi-dimensional definition of complexity for industrial systems, which is expressed by a set of hypotheses.

As a next step the following chapter now introduces the chosen research philosophy, methodology and paradigm to achieve the defined aim, objectives and to answer the MRQ and the SRQs and to fulfill O1-O4.

# 8 Research methodology

This chapter now describes the underlying philosophy, applied methodology and paradigm to achieve the research goal and objectives of this thesis and has the goal to provide an in-depth discussion and definitions of the applied methodological framework.

To achieve this, this chapter discusses and defines the applied research philosophy, research methodology, research paradigm and thus how a SMTT for strategic complexity management can be developed and applied on real-world industrial systems in a coherent methodological framework.

The structure of this chapter is that it starts with classification of the research philosophy on a meta-level, proceeds with the introduction of the research methodology and proceeds with the presentation of the methodology applied for the operationalization of the research and concludes with the applied research paradigm for the development of a strategic complexity management framework (SMTT) and its application on real-world industrial systems via a multi-case study approach.

The chosen research framework is oriented on the complexity management case study research design as showcased by Myrodia (2016), Ardolino et al. (2018), Fernandez et al. (2019), Gorod et.al. (2014) and Anderson et al. (2005). Figure 39 now shows the applied framework of research philosophy, methodology and paradigm and how they are connected in a hierarchical order. The chosen research framework is based on the so-called "ladder of knowledge" dedicated for complexity management as proposed by Mariotti & Zauhy (2013).

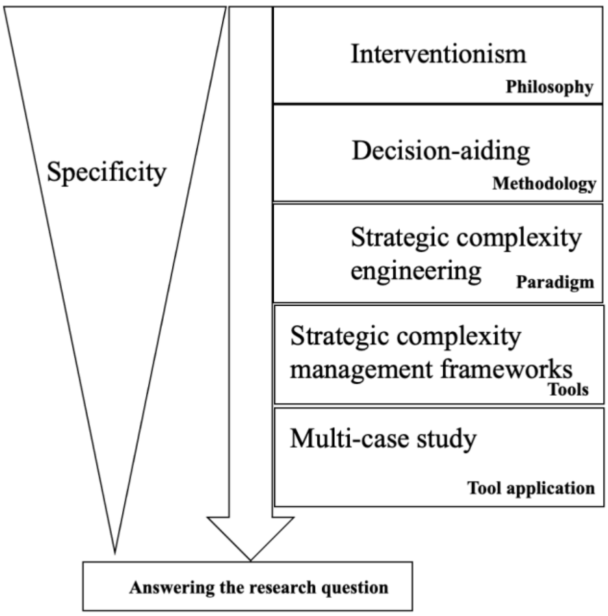



*Figure 39: Research methodology overview*

Figure 39 shows that the chosen research philosophy for this thesis is interventionism, the corresponding methodology is decision-aiding, and the resulting paradigm for framework establishment is strategic complexity engineering. The developed strategic complexity management framework will then be applied and evaluated based on multi-case study research.

Consequently, the next section now describes the research philosophy of *interventionism*.

## 8.1 Research philosophy: interventionism

The research philosophy of interventionism can be regarded as a cluster of subjectivistic research approaches where the researcher deeply immerses herself with the object of her study. (Jönnson et al., 2005)

To avoid confusion, a research philosophy shall be defined as a system of beliefs and assumptions concerning the development of knowledge in the scientific process. (Saunders et al., 2009)

In the case of interventionism, it shall be true that the researcher is directly involved with the system under investigation. Out of this immersive approach results a situation in which the researcher accepts a lack of control over her research design and acts on the situation in concert with the host organization of the system, while analysing findings. (Jönsson et al., 2005, Woodward, 2014)

The researcher therefore aims to refute an objective perspective on the object of research and becomes an insider of the world that is researched. It can therefore be stated that interventionistic research can be regarded as an umbrella concept that can incorporate different types of research approaches, such as action research, case study research or constructivist research.  (Jönnson et al., 2005)

The core theoretical assumptions of interventionism are well summarized by Woodward (2014) who proposes a characterization where interventionism is defined as an intervention on a given variable X (e.g., complexity) with respect to variable Y (e.g., a system performance).

This interventionism causes a change in the value of X (e.g., complexity) which is such that the value of Y (e.g., system performance) changes if at all via a route (or routes) that goes through X (e.g., complexity) and not in some other way.

Based on Woodward (2014) interventionism thus assumes two propositions to be the case:

- **Intervention:** It exists a commitment to the possibility of intervening on X.
- **Effect:** It exists a claim about what would happen to Y under such an intervention.

Based on these statements the next section now covers the four general principles of intervention research.

### 8.1.1 General principles of intervention research

To further illustrate the reasoning behind intervention research, the following general principles of intervention research, based on David (2002) can now be introduced:

- **Understanding:** The aim is to gain an in-depth understanding of the way in which the system operates, to help it to define possible paths for change, to help it to choose one, to implement it and evaluate the results.
- **Knowledge:** Knowledge is produced in interaction with the field, but takes a special, delocalized position.
- **Theory:** The researcher runs through different theoretical levels or dimensions of analysis.
- **Scientific principles:** The normative position of intervening with reality is justified with reference to scientific principles (search for the truth) and democratic principles (equal respect for all actors).

The four principles show that intervention research enables the formalization and contextualization of models and management tools to progress in an interactive manner.

In the context of complex systems of organized complexity, Heino et al. (2021) state that there is a growing interest in the development of intervention models that explicitly model complexity by the current research community.

As a next step, the next chapter defines the methodology of decision-aiding as a methodological approach of interventionism in managerial science.

## 8.2 Interventionism in the managerial sciences: decision-aiding

As indicated, decision-aiding shall be regarded as the chosen methodology in the context of the philosophy of interventionism.

To again avoid confusion, a research methodology shall be defined as how a scientific investigation to obtain knowledge shall be executed in terms of reasoning, learning, and investigating in the constraints of the research philosophy. (Woodward, 2014)

In general, it can be stated the decision-aiding approach represents a "de-optimization" of classical operational research. (Roy, 1996, Montagna, 2011)

The proposed application of decision-aiding and the utilization of tools in the context of complex systems decision-making for this thesis furthermore draws upon the propositions of Yurtseven & Buchanan (2016), Montagna (2011), Gorod et al. (2014), Bigaret et al. (2017), as well as Le Bris et al. (2019).

The relation of prescription expressed by the concept of decision aiding breaks away from the idea of traditional "decision-making science" in the sense of not being a normative approach enabling a prescription of the "best rational decision" which is independent of the actors and the organizational context. (Roy,1996)

Roy (1996) shows that it is impossible to uphold this normative position in concrete situations and supports the idea of a "science of decision aiding", that helps to obtain more subjective responses to the questions posed by a stakeholder of the underlying decision process.

The research of Montagna (2011) furthermore illustrates the applicability of this approach in the context of complexity management and emphasizes the value of developing and applying appropriate decision-aiding tools and processes in the context of complexity management.

The next section now describes the decision-aiding process.

### 8.2.1 The decision-aiding process

According to Tsoukias (2007) the decision aiding process consists out of a decision-maker, who deploys a decision-theoretic tool, for example a SMTT, to establish potential actions to undertake to solve a problem for a “client”, who is often a corporation / host organisation. In such a setting, a researcher is functioning as an “analyst” and supports the decision-maker, in this case regarded as the “client”, to deploy said tool.

In this context a decision-aiding model or tool shall be defined according to Roy (1996), namely that as a model that is applicable to a certain family of questions and that is considered as a representation for a given class of phenomena of a posed problem.

In general, any decision-aiding model can only relate to a fragment of reality. Such a fragment is to be considered as a functioning system that can be isolated in a manner consistent with its intended purpose. The fragment of reality is, therefore, specified both by the way it relates to a certain class of phenomena and by the purpose of the family of questions to be addressed. (Roy, 1996, Montagna, 2011, Bigaret et al., 2017)

Consequently, decision-aiding is to be regarded for the purpose of this thesis as a specific form of model/ tool-based client-analyst interconnected decision-making to solve a given client problem in respect to a given industrial system located at the host organisation.

This leads to the conclusion that decision-aiding situations appear in the interaction space of at least two actors: the client and the analyst.

This interaction space is characterized by a meta-object which is the consensual reconstruction of a client´s concern, the decision-problem to be solved. (Tsoukias, 2007)

Figure 40 now illustrates the concept of the decision-aiding process.

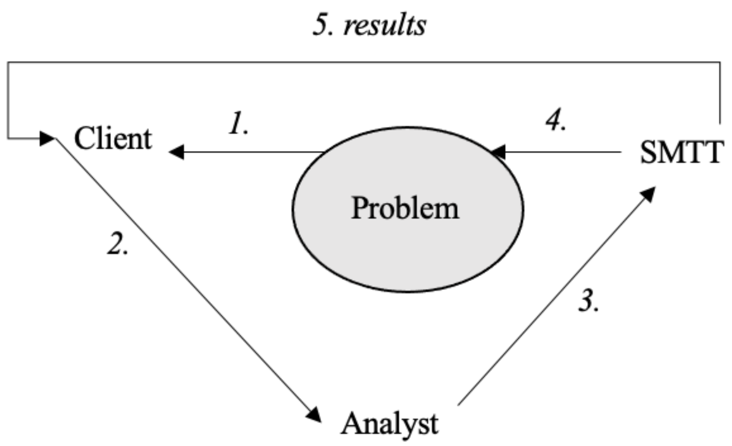



*Figure 40: The process of decision-aiding*

Figure 40 makes visible, that the decision-aiding process is to be regarded as a highly subjective problem-solving approach based on the utilization of SMTTs for a pre-defined client / analyst interaction space that contains the consensual reconstruction of a client concern, namely a problem and a problem solution in the form of results.

In general, the process can be outlined as the following:

A problem for a client exists (1), this problem is given to an analyst (2), the analyst applies a SMTT fitting to the consensual problem reconstruction (3), the SMTT is applied on the problem (4), results are obtained by the client (5) through the analyst.

After the describing the process of decision-aiding in general, the next section further expands on how different approaches of decision-aiding can manifest.

### 8.2.2 Decision-aiding approaches

According to Tsoukias (2007) four different approach of decision-aiding can now be identified.

- **Normative:** Deriving of models based on *a priori* norms. Deviations from these norms are to be regarded as mistakes by the client. These models intend to be universally applicable to all clients who want to behave rationally in the context of the applied decision-making model.
- **Descriptive:** Deriving of models based on real-world observations how decision-makers make decisions.
- **Prescriptive:** A prescriptive approach aims to provide answers to a problem based on the assumptions of limited information and is thus closely related to heuristics.
- **Constructive:** Based on an *a posteriori* discussion of analyst and client to construct a model based on the view of the client. It is important to mention that the interaction between client and analyst is to be regarded as part of the decision-making process.

This shows that work in decision aiding is focused directly on knowledge, potentially even independent of relations between the client and analyst. It is important to mention at this point, that the described approaches are not to regarded as necessarily exclusive to each other, monistic, and can be combined with each other to achieve pluralistic, hybrid approaches being both *a priori* and *a posteriori*.

For example, it could be possible to apply a heuristics-based prescriptive approach while applying a priori normative decision rules or strategies. (Tsoukias, 2007, Montagna, 2011)

Montagna (2011) state in this context, that hybrid approaches and hybrid decision-aiding tools are particularly valuable models for managerial decision-making when faced with complexity. For example, a SWOT matrix SMTT can be regarded as a prescriptive, normative, hybrid decision-aiding tool, since it aims to provide answers to a problem based on limited information which then allows to derive norm strategies which the client should apply and where deviations are to be regarded as strategic mistakes in the context of the SWOT matrix.

In this context, Roy (1996) states that the construction and the use of such a model force the analyst to introduce a set of so-called *voluntary hypotheses*.

These are hypotheses that, by definition, could not be proven true or false, either because no conclusive tests could be designed or because they are imposed as policy / axioms. These hypotheses concern the values of certain model parameters (interest rates, growth rates, timing of a future event etc.) or the dimensions of the model itself (consideration of certain scenarios, definition of decision variables, causal variables and data, existence, and nature of a relationship etc.). Consequently, the development of a set of voluntary hypotheses is to be regarded as the predisposition of any tool application.

The next section now introduces the artefacts which are contained in the decision-aiding process.

### 8.2.3 Artefacts of the decision-aiding process

The decision-aiding process shall now contain the following core artifacts, based on the research of Tsoukias (2007), Bisdorff et al. (2015) and Montagna (2011). These are described in Table 10.

*Table 10: Decision-aiding artefacts*

| **Artefact** | **Description** |
|---|---|
| Representation of the problem situation | Aimed at answering the following questions:<br>• Who has a problem?<br>• Why is this a problem?<br>• Who decides on the problem?<br>• Who is responsible for the consequences of a decision?<br>The problem situation shall be defined as the following triplet:<br>P= (A, O, S)<br>*Where:*<br>• A is the set of participants to the decision process.<br>• is the set of stakes each participant brings within the decision process. |

| | |
|---|---|
| | • S is the set of resources the participants commit on their stakes and the other participants' stakes. |
| Problem formulation | A problem formulation reduces the reality of the decision process in which the client is involved to a formal and abstract problem. The result is that now formal and abstract methods can be applied to study the situation.<br>The problem formulation shall be defined as the following triplet:<br>F= (W,V,N)<br>*Where:*<br>• W is the set of potential actions the client may undertake within the problem situation as represented in P.<br>• V is the set of points of view under which the potential actions are expected to be observed, analyzed, evaluated, compared, including different scenarios for the future.<br>• N is the problem statement, the type of application to perform on the set A, an anticipation of what the client expects. |
| Evaluation model | An evaluation model shall be defined as an n-uplet.<br><br>M= (A, (D,E),H,U,R)<br>*Where:*<br>• A is the set of alternatives on which the model applies. It establishes the universe of discourse of all relations and functions which describe the client´s problem.<br>• D is the set of dimensions under which the elements of a are described, measured, or observed.<br>• E is the set of scales associated to each element of D.<br>• H is the set of criteria under which element of A is evaluated.<br>• U is the set of uncertainty structures or epistemic states applied on D and H.<br>• R is a set of operators such as information available on A. R can be synthesized to a more concise evaluation through D and H allowing a final recommendation. |

| | |
|---|---|
| Final recommendation | Represents the return to reality in the decision-aiding process and a result will be produced by the evaluation model. The final recommendation now translates the abstract and formal language of the model to the current language of the client.<br>Some elements are very important in constructing this artifact:<br>• The analyst must be sure that the model is formally correct.<br>• The client must be confident that the model represents all preferences, that one understands it and that one should be able to use its conclusions.<br>• The recommendation should be "legitimated" with respect to the decision process for which the decision aiding has been asked. |

Figure 41 now summarizes how the different artifacts of decision-aiding are connected to each other based in the context of a SMTT application.

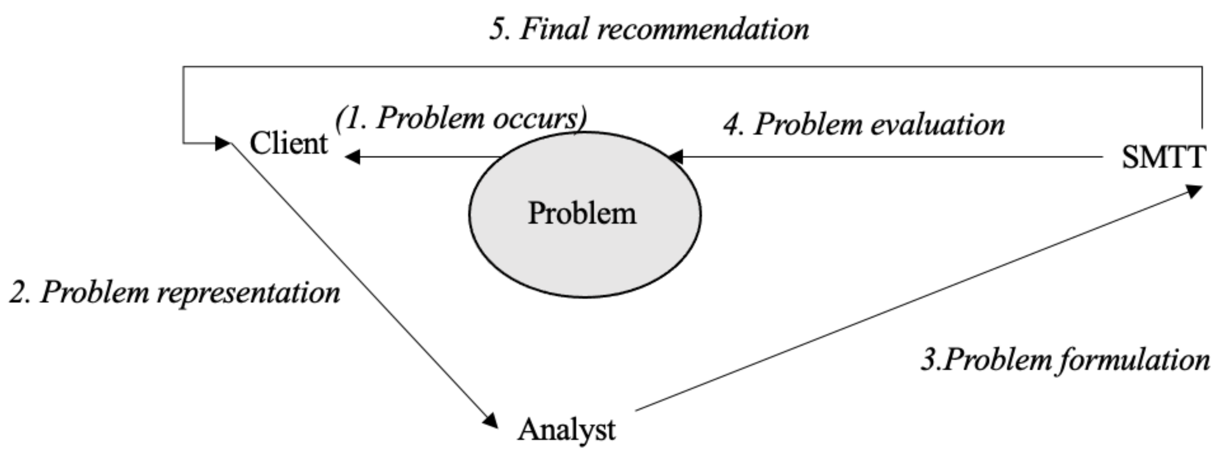



*Figure 41: SMTT application in the context of decision-aiding*

Figure 41 showcases that decision-aiding now must be regarded as subjective problem-solving approach that is limited by the capacities of the ability to adequately reconstruct the problem in terms of representation and formulation, by the choice of SMTT as the evaluation model in the process of problem evaluation and by ability to translate the problem evaluation into a final recommendation.

Nevertheless, to highlight the relevance of the decision-aiding approach for the research question of this thesis, Montagna (2011) state that especially two issues must be considered when it comes to deploying decision-aiding artefacts for complexity management:

- The breaking down of the problematic situation into the relevant aspects.
- The use of new tools because classical tools (optimization methods, statistical tools, etc.) on their own are insufficient to face a problem.

The next section now describes how intervention and decision-aiding research is to be conducted in practice by introducing the case study approach as the chosen research method for the operationalization of interventionism and decision-aiding for this thesis.

## 8.3 Research operationalization: case study approach

Based on the mentioned characteristics of interventionism and decision-aiding the case study approach is often the most approachable research method for this kind of research. This is reenforced by the complex system case study research conducted by Gorod et al. (2014) and as shown the context of complex system decision-aiding case study research by Daniell et al. (2010).

For clarification, a research method shall be defined as the planned procedure to find an answer to a research problem and guides data collection and evaluation. (Saunders, 2009)

According to Baard (2010), in the case of interventionism often results a research methodology based on case study research, whereby researchers involve themselves in working directly with managers in organizations to solve real world problems by deploying theory for designing and implementing solutions through interventions and analyzing the results from both a theoretical and practice perspective.

Therefore, interventionistic research is not focusing on providing explanatory theories on an objective conceptual level but aims to test, illustrate or to refine existing theory by intervening and interfering in the object of research. (Jönsson et al., 2005)

Based on the displayed information, interventionism can now be regarded as broad term for a wide cluster of research approaches that often manifest in a case study approach.

As a result, interventionistic research can be regarded as a highly subjective, interpretative case study approach that refutes the idea of objective observation and replaces it by an immersive in vivo approach in which the researcher observers the research object whilst being part of the object itself.

Thus, it is required of a non-pragmatist researcher to belief in the importance and effectiveness of active involvement through intervention and to employ the necessary skillset to make this approach effective since researchers can never be separate from their own values and beliefs, so these will inevitably inform the way in which they collect, interpret, and analyse data. (Baard, 2010)

The next section now provides a general definition of the case study approach.

### 8.3.1 A general definition of the case study approach

According to Harrison et al. (2017) the case study research has grown in reputation and is seen as an effective methodology to investigate and understand complex issues. The main advantages of this approach are its functionality in real world settings and its usability in a high number of disciplines, particularly the social sciences, education, business, law, and health, to address a wide range of research questions. Case study research is described as a versatile form of qualitative inquiry most suitable for a comprehensive, holistic, and in-depth investigation of a complex issue (phenomena, event, situation, organization, program individual or group) in contexts, where the boundary between the context and issue is unclear and contains many variables. (Harrison et al., 2017)

Yamashita & Moonen (2014) state in this context that case studies can deal with complex causal relations and complex interaction effects. They furthermore state that case studies enable the in-depth study of detailed causal mechanisms.

A case study shall now be conclusively defined for this study as proposed by Gustaffson (2017), namely as an analysis of systems that are studied with a comprehensive view by either one or several methods.

Beside the variety of case study-based research opportunities, the case study approach has common characteristics.

The following Table 11 gives an overview about the by Harrison et al. (2017) defined elements of case-study based research, their description, and the transfer of the research on a given research object.

*Table 11: Case study elements*

| **Elements** | **General description** |
| --- | --- |
| The case | • Object of the case study identified as the entity of interest or unit of analysis<br>• Program, individual, group, social situation, organization, event, phenomena, or process |
| A bounded system | • Bounded by time, space, and activity<br>• Encompasses a system of connections<br>• Bounding applies frames to manage contextual variables<br>• Boundaries between the case and context can be blurred |
| Studied in context | • Studied in its real life setting or natural environment context is significant to understanding the case<br>• Contextual variables include political, economic, social, cultural, historical, and/or organizational factors |
| Selecting the case | • Based on the purpose and conditions of the study<br>• Involves decisions about people, settings, events, phenomena, social processes<br>• Scope: single, within case and multiple case sampling<br>• Broad: capture ordinary, unique, varied and/or accessible aspects<br>• Methods: specified criteria, methodical and purposive, replication logic, theoretical or literal replication |
| Multiple sources of evidence | • Multiple sources of evidence for comprehensive depth and breadth of inquiry<br>• Methods of data collection: interviews, observations, focus groups, artifact and document review, questionnaires and/or surveys<br>• Methods of analysis: vary and depend on data collection methods and cases; need to be systematic and rigorous |
| Case study design | • Descriptive, exploratory, explanatory, illustrative, evaluative, single or multiple cases<br>• Embedded or holistic |

| | |
|---|---|
| | • Particularistic, heuristic, descriptive, intrinsic, instrumental, and collective |

After defining the case study method in detail, the next section now discusses the multi-case study approach.

### 8.3.2 Multi-case study approach

According to Campbell et al. (2018), a case study can contain either a single study or multiple studies. The researcher therefore must consider if it is sensible to make a single case study or if it is more appropriate to analyse multiple cases for the understanding of the phenomenon. It is explained that when the researcher chooses to do a multiple case study it is possible to analyse the data within each situation and potentially across different situations, unlike when a single case study is chosen, and strong and reliable evidence can be created.

In general, it can be stated that if a multitude of cases is selected and analysed, a multi-case study approach is resulting.

Thus multiple-case designs may generally be preferred over single-case designs since the analytic benefits from having two or more cases may be substantial. (Campbell et al., 2018)

The next figure illustrates the multi-case study approach.

Based on Campbell et al.  (2018), Figure 42 illustrates the multi-case study approach.

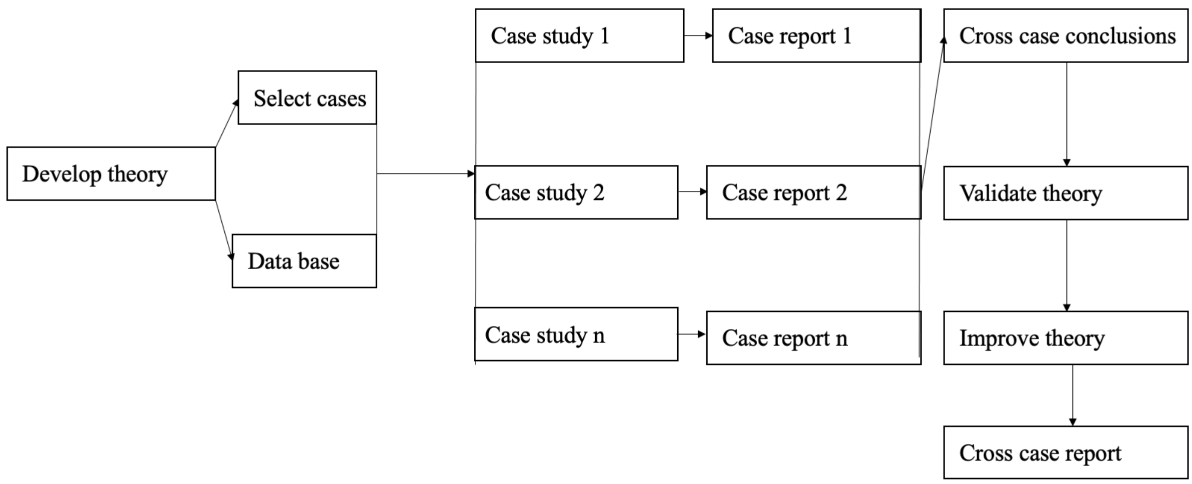



*Figure 42: Multi-case study design*

Figure 42 shows that the multi-case study approach combines several case studies to explore and improve a developed theory.

The multi-case study approach is thus based on cross case comparison and conclusions which aim to make the derived individual case conclusions more reliable and stronger and can be regarded as the preferred approach to the single-case study.

The next section now briefly expands on the benefits and limitations of the case study approach.

### 8.3.3 Benefits and limitations of case study research

This section now briefly introduces and discusses the benefits and limitations of case study research.

Yamashita & Moonen (2014) identify the following core benefits to case study research:

- Potential for higher results validity
- Strong procedures for fostering new hypotheses
- Reasoning about causal mechanisms in individual cases
- Capacity to address causal complexity

In the context of complex industrial systems and the application of management tools the value of such case studies does not only lie in the development of a repository of well-documented examples but also in the potential to discover patterns that provide insight into what works and what does not work and into what circumstances produce which result. (Stevens, 2006)

Yamashita & Moonen (2014) identify the following core challenges in case study research:

- Selection of cases and bias due to case availability
- Determining relative causal weights for variables of analysis

This shows that many studies examine multiple cases involving systems with different functionality and contexts, which hinders the comparability of cases. One of the main underlying reasons is that it is difficult to identify, and get access to, multiple cases with the necessary characteristics.A similar challenge applies to determining the relative causal weighs of variables. Case studies are often better at assessing whether and how a variable mattered to the outcome rather than how much it mattered. (Yamashita & Moonen, 2014)

In the light of these challenges, it is thus necessary to state for this study that the cross-case comparability of cases in a multi-case study research design is to be regarded as limited in general and most emphasis to is be positioned on the knowledge obtained in individual cases.

As a next step, the section to follow now describes how the chosen paradigm for the establishment of a strategic complexity management framework.

## 8.4 Paradigm to establish a strategic complexity management framework

After introducing the underlying research philosophy, methodology and the multi-case study approach a consistent definition of a strategic complexity management paradigm for complex industrial systems shall now be established to allow a methodological and scientific pursuit of the actual establishment of a SMTT for strategic complexity management for industrial systems.

Such a paradigm shall be based on a set of axioms defined to establish the goals of strategic complexity management before introducing the paradigm itself. To avoid misconceptions, a paradigm shall now be defined as a basic belief system and theoretical framework with assumptions about ontology, epistemology, methodology and methods for a given scientific purpose. It is thus a research approach of understanding reality and studying it and shall guide the development of the proposed SMTT in later chapters of this study. (Rehman & Alharti, 2016, Mariotti & Zauhy, 2013)

### 8.4.1 Axioms of strategic complexity management

Based on the thoughts of Frizelle et al. (2000), Stevens (2006) and in line with Rosser´s (2019) propositions, strategic complexity management shall primarily concern itself with the following aspects which are to be regarded as the core axioms of strategic complexity management for this thesis.

These axioms are now defined in detail in the next Table 12.

*Table 12: Axioms of strategic complexity management*

| Axiom (A) | Description |
|---|---|
| **A1: Acknowledge**<br>Complexity must be acknowledged.<br>- Complexity hypotheses | This axiom requires to recognize non-deterministic behaviour in complex industrial systems. It means:<br>• Recognizing that industrial systems are difficult to comprehend because of complex system behaviour. This means understanding how the parts of a system give rise to the collective behaviours of the system.<br>• Recognizing that many industrial systems can be classified as complex systems, because they exhibit degrees of self-organization, |

| | |
|---|---|
| | emergence, innovation, learning and adaptation.<br>• Establishment of hypotheses how complexity may work in industrial systems. |
| **A2: Characterize**<br>Complexity must be characterized.<br>- Complexity model | This axiom focuses on learning about where the complexity is coming from and what kind of complexity it is. It means:<br>• To acknowledge that the study and modelling of such systems requires metaphors and models that can theoretically capture the in A1 hypothesized complexity characteristics and complexity sources. |
| **A3: Anticipate & Manage**<br>Complexity must be anticipated and managed.<br>- Heuristics-based framework | This axiom is achieved by broadly anticipating practical complexity manifestations and applying strategies to manage their impact. This means:<br>• To acknowledge that the strategic management of complex industrial systems can require the strategic application of heuristics, in the form of SMTTs to allow effective decision-making.<br>• Recognizing that an effective SMTT for strategic complexity management must be based on the results generated in order to fulfil A1 and A2.<br>• Recognizing that practical application not theory drives the development of processes and tools for strategic complexity management for complex industrial systems. |

The axioms A1-A3 show that strategic complexity management shall be regarded as neither an overarching science or philosophy nor a specified singular individual technique from a methodological point of view. It is thus to be regarded as a distinct methodology of strategic corporate thinking with a set of connected decision-aiding techniques and methods which allow decision-makers to view and influence industrial systems of economic value creation through the perception of industrial systems as complex systems that can have emergent behaviour and can be strategically managed via heuristics in the form of SMTTs.

A1-A3 are now serving as the paradigmatic baseline for the development of a paradigm for strategic complexity management that defines the nature and requirements of the scientific inquiry of establishing such an SMTT and thus the scientific inquiry of this study.

### 8.4.2 The paradigm of strategic complexity engineering

This section now introduces a paradigm for a coherent strategic development and application of strategic complexity management frameworks in the context of industrial systems for this thesis which allows the defined axiom A3 to be scientifically captured and practically pursued and manifested.

According to Frei & Serugendo (2011) complexity engineering aims at the concrete use of complexity inspired methods for practical systems engineering of industrial systems.

Buchli & Santini (2005) state in this context that in complexity engineering it is especially important to look at different systems and their underlying principles from the point of practical application.

The goal of looking at a system with the goal of applying complexity inspired methods for practical and strategic systems engineering of industrial systems shall be defined by the overarching term of *strategic complexity engineering.*

Based on the propositions of Frei & Serugendo (2011) modern industrial systems exhibit three main research directions in which the perspective of complexity can contribute to the development and integration of modern industrial system, like CPS, to achieve economic value creation. These are the directions of philosophical value, instrumental scientific value, and instrumental practical value and can be described as the following:

- **Philosophical value**: A unified and structured body of knowledge, is generated through the analysis of the nature of complexity and the establishment of corresponding voluntary hypotheses to capture and better understand the general phenomenon of complexity in the context of the system to be analysed and managed.
- **Instrumental scientific value:** Results from the establishment of a model of complexity to capture and analyse a given engineering problem based on the structured body of knowledge in the form of the hypotheses established.

- **Instrumental practical value**: The value of answering to material economic needs is generated through the development and practical application of dedicated SMTTs which are based on the assumptions of the model generated, thus fulfilling the defined core premise of strategic complexity engineering.

Consequently, it can be stated that the in the provided paradigm the system dependent complexity phenomenon is regarded as the causal source for the resulting engineering problem which is again the causal source for the resulting strategic opportunity.

The phenomenon is assumed to be captured by a system dependent definition of the nature of complexity. The resulting engineering problem is then captured through the means of a complexity model and the respective strategic opportunity can be captured through the application of dedicated SMTTs.

Consequently, the research direction of understanding complexity as a strategic opportunity can be regarded as the most comprehensive and ambitious approach to integrate complexity science into a context of industrial economic value creation.

It is shown that any practical strategical application of complexity via strategic complexity management SMTTs requires to be based on a complexity model which is in turn based on a conception of the nature of complexity in the form of *voluntary hypotheses* related to the respective context of analysis.

The presented paradigm of strategic complexity engineering shall now be regarded as an overarching scientific paradigm that governs the pursuit of the establishment of a strategic complexity management SMTT in the form of a strategic complexity management framework (SCM).

Therefore, the next part of this thesis concerns itself with developing a conception of the nature of complexity in the respective context of complex industrial systems to fulfil the first axiom of strategic complexity management: *Acknowledging complexity* and to answer SRQ1 /O1.

# 9 Hypotheses concerning the nature of complexity in industrial systems

To fulfil SRQ1 and O1 of this thesis, the first axiom of strategic complexity management, *acknowledging complexity* is now approached in this chapter. This is achieved through introducing a detailed analysis concerning the nature of complexity as an emerging phenomenon in complex industrial systems and its impact on the decision-making process.

A novel set of *voluntary hypotheses* (as defined by Roy (1996) defined as hypotheses that by definition, cannot be proven true or false, either because no conclusive tests could be designed or because they are imposed as policy) concerning the nature of dynamic complexity as the core obstacle to the performance in industrial systems is introduced, as shown in the research of Freund & Al-Majeed (2021a). These voluntary hypotheses serve as foundational assumptions concerning the nature and therefore the behaviour of complexity in industrial systems for all further inquiries conducted in this thesis.

The intellectual basis for the analysis conducted in this part is provided by the Stevens (2006) who proposes three dimensions of analysis for complex industrial systems via a dedicated framework for the exploration of such systems.

Figure 43 now illustrates the framework proposed by Stevens (2006).

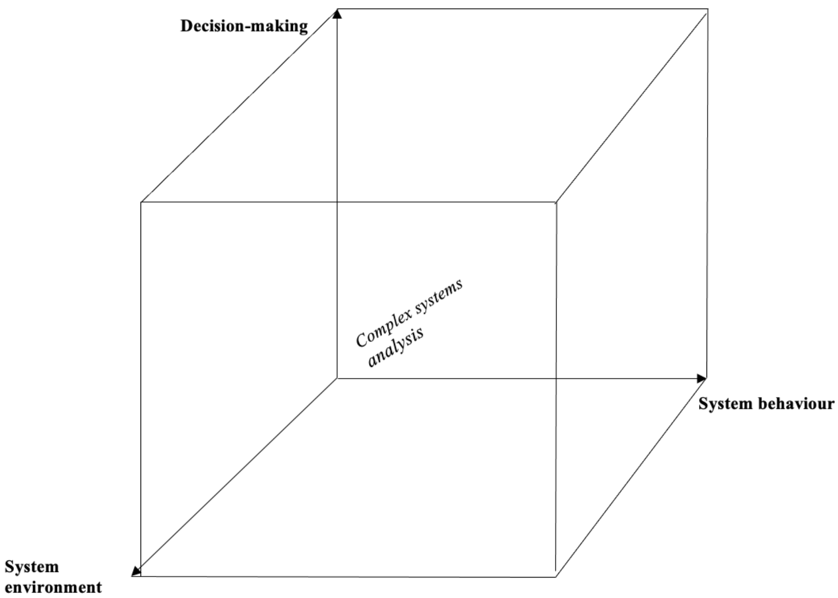



*Figure 43: Dimensions of analysis for complex systems*

Figure 43 shows that three dimensions are necessary to explore, namely *system behaviour, decision-making*, and *system environment*.

Consequently, the analysis and voluntary hypotheses presented in this part strongly refer to these dimensions of analysis to establish voluntary hypotheses that function in a well-organized, combined, and synergistic manner. To avoid confusion, an hypothesis in general shall be defined for this thesis as a first tentative explanation of the research problem and comes close to an *educated guess*.

The next section now focuses on the dimension of the behaviour of complex systems in the form of dynamic complexity.

## 9.1 Complex system behaviour

As already shown, it is possible to introduce the definitions of static complexity and dynamic complexity for industrial systems. Static or structural complexity can be defined as how the industrial system is structured (e.g., number of processors/machines, machine connections). In this case the static complexity refers to the constellation of information sources and their reflexive and irreflexive relations between them in a CPS.

Dynamic complexity shall be defined as a time-dependent, information-based measure of the unpredictability in the behaviour of the system over a time-period. A common example of dynamic complexity is any type of unwanted system behaviour, like a machine breakdown. (Deshmuk et al., 1998) Dynamic complexity represents the core obstacle to achieving the systems target function and shall be the focus of the line of argumentation of this chapter. (Mourtzis, 2019) The focus of this section lies therefore on the application of the concept of dynamic complexity on CPS and does not consider static complexity metrics or system external complexity influence factors at this point in the thesis to provide to avoid confusion.

As a starting point the term “information” is now defined for the context of this thesis.

### 9.1.1 A definition of information

It is necessary to state that the term “information” is itself to be regarded as a polymorphic phenomenon and a poly-semantic concept with many possible meanings. The term “information” is now defined for this thesis according to the notions established by Meijer (2013) under the assumption that information is generated through the interactions of a set of communicating agents. The term information shall therefore be defined as anything that an agent can sense, detect, observe, perceive, infer or anticipate.

To make this statement clearer, the term agent is now defined in more clarity.

### 9.1.2 Agents

An agent shall be defined according to Meijer (2013) as a description of an entity that acts on its environment. Note that agents and their environments are also information, as they can be perceived by other agents. An agent can be an electron, an atom, a molecule, a cell, a human, a computer program, a market, a machine, an institution, a society, a city, a country, or a planet. Each of these can be described as acting on their environment because they interact with it.

According to Monostori et al. (2006) an agent operates in an environment from which it is clearly separated.

In this constellation an agent does the following things:

- It makes observations about its environment.
- It has its own knowledge about its environment.
- It has preferences regarding the states of the environment.
- It initiates and executes actions to change the environment.

Agents operate in environments that are only partly known, observable and predictable. Autonomous agents have the opportunity and ability to make decisions of their own. Rational agents act in the manner most appropriate for the situation at hand and do the best they can do for themselves. These agents maximize their expected utility given their own local goals and knowledge. Rationality can be bound by the complexity of a decision problem, the limitation of resources, or by both. An agent with optimization objectives but with limited means is a bounded rational agent. (Monostori et al., 2006)

The following Figure 44 now describes the relationship of agent / environment.

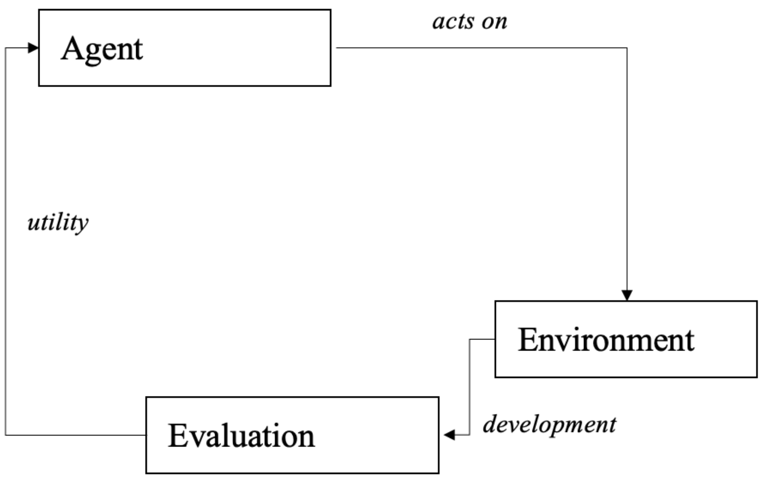



*Figure 44: Relationship agent / environment*

In a rudimentary sense, an agent shall be able to act on its environment in three ways: (Burgin, 2009)

- **Receptor:** Agent receives raw information, “data”, from its environment
- **Processor:** Agent processes received data to descriptive information
- **Effector:** Agent transfers descriptive information to other agents in the form of prescriptive information

In this light, it is important to mention that strategic complexity engineering thus acknowledges the presence and action of “autonomous agents” as important elements which must either be eliminated or augmented by applying a set of tools to deal with their existence as interconnected system elements. (Norman, 2004)

The next section now defines the term system.

### 9.1.3 System

A system is now defined as the concept of portioning an operating entity into a set of interacting units with specific relationship among them. A system therefore represents not only physical, spatial objects but also immaterial, temporal concepts like information and can maintain both system external and system internal interactions. (Jalil & Perc, 2017, Mourtzis et al., 2019)

Consequently, for the purpose of this thesis a system is regarded as an open adaptive industrial manufacturing system if not defined otherwise. Based on this statement a system is defined as a production network of a given number of agents which are characterized by the ability to interact with each other and the system external world by transferring, storing, and circulating information in the network topology in order to produce marketable products.

A network therefore comprises a system of at least two elements in the form of agents that are connected and that exchange information between them and the system external world. Such a system shall be characterized by three invariant properties, as defined by Fromm (2004).

- Communication and complexity by specialization and cooperation between agents
- Adaptation, feedback, growth and reproduction of information
- Spatial and temporal organization

Such a system shall therefore be defined as a *complex adaptive system* (CAS).

Based on these notions the next section now further defines the concept of agents in a system.

### 9.1.4 Agents in a system

Figure 45 now summarizes and illustrates the ways an agent can act on its environment in more detail by providing a simple example in which two agents (A1 and A2) circulate information in a system and thus forming a complex adaptative system (CAS). (Fromm, 2004)

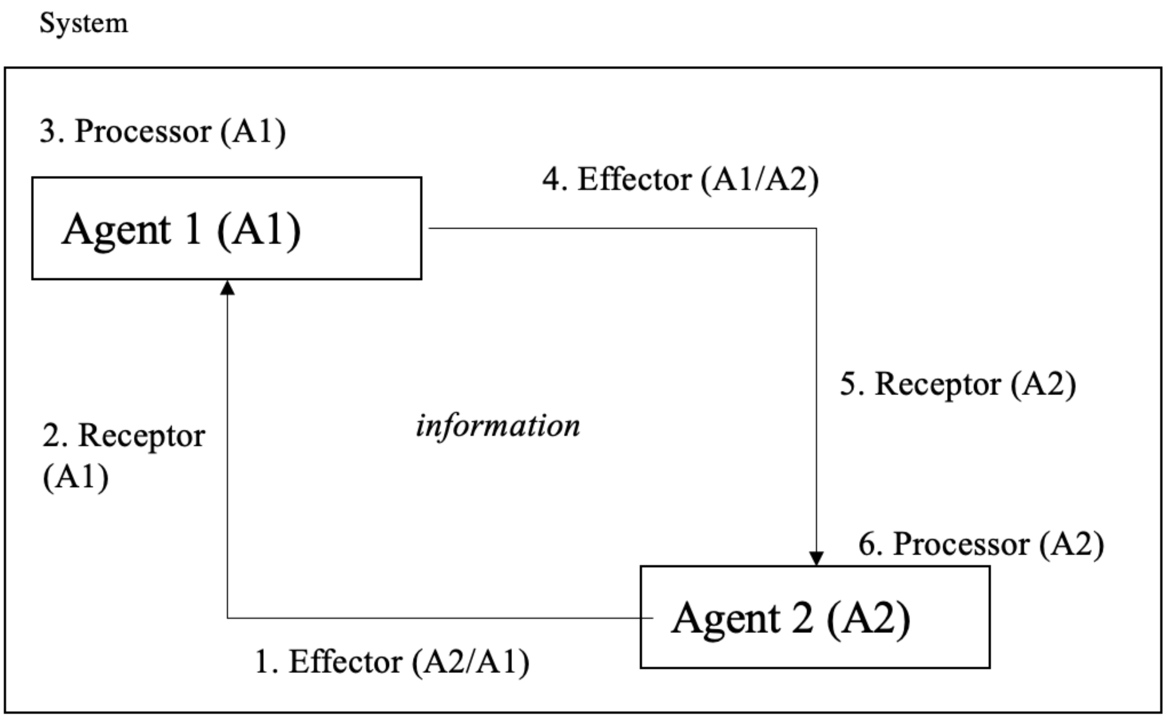



*Figure 45: Basic structure complex adaptive system*

In relation to Figure 45, Figure 46 shows a possible conceptual classification of agents as either biological, robotic, and software agents. (Park & Tran, 2017)

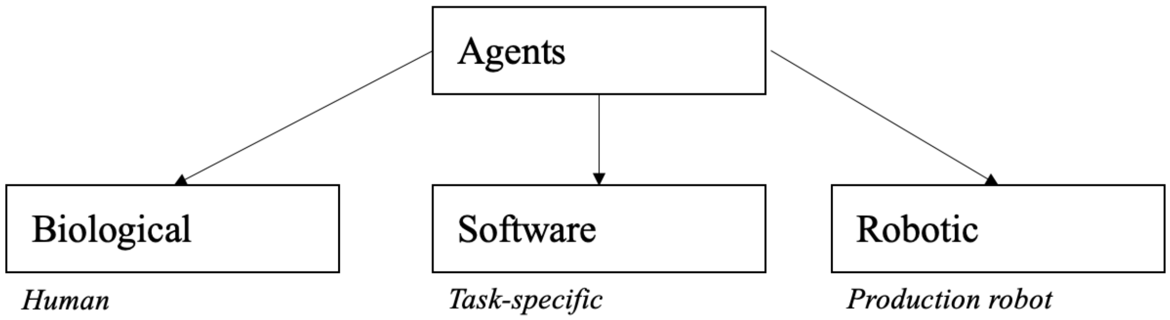



*Figure 46: Types of agents*

Consequently, an agent in a system can be defined for this thesis as either a human, a task-specific software or a production robot when defined in a manufacturing system.

The idea of the environment of an agent, the system, is defined as concept of that the environment of an agent consists of all the information interacting with it. (Meijer, 2013)

The environment of an agent shall from this point onwards be regarded as a near-synonym of the term “system”.

The term “data” is now described as the basic individual items of information, obtained and conserved through observation and data storage but devoid of an attributed context. There are many kinds of data existing, like sensory data, geographical data or network data. (Duan et al., 2019)

As a logical consequence of the presented definitions of the term data and information the relationship of data and information can be described as the following concept:

*Data + storing / recovering by an agent / set of agents in a given environment → Information*

Consequently, any form of stored and recoverable data through the means of an agent in a system via the described receptor, processor and effector logic shall be regarded as information. This results in the core assumption that if data is stored and recoverable in any given form it shall be regarded as information.

The relationship of agents, data and information can be defined on the basis for Hypothesis 1 (H1).

### 9.1.5 Hypothesis 1: Agent based information and data hypothesis

**(H1)** *The amount of information in a system is represented by the amount of data stored and recoverable by agents contained in the system.*

After introducing H1 the next section now discusses the how agents can function as sources of information in an industrial system.

### 9.1.6 Agents as sources of information in a CPS

To further expand on the statements made, it is possible to classify the following agents and agent combinations as major sources of information under the assumptions of a modern, interconnected technological environment or multi-agent system. (Duan et al., 2019, Gimpel & Röglinger, 2015)

The following sources of information in the form of agents are hypothesized for this thesis and are displayed in Table 13.

*Table 13: Agent types*

| Agents | Description |
|---|---|
| Machine generator (M) | Autonomously generated by machine activity through sensors and instruments, for example the amount of information generated and stored by a smart factory or an artificial intelligence. |
| Machine-machine generator constellation (MC) | The combination of autonomously generated by machine activity through sensors and instruments that processed by another machine, for example the amount of information generated and stored by a smart factory that is again processed by an artificial intelligence. |
| Human generator (H) | Generated by human activities, for example a poem memorized by the human brain that generated the poem. |
| Human-human generator constellation (HC) | Generated by human activities, for example a poem memorized by the human brain that generated the poem and that is also memorized by the other human brains. |
| Human-machine generator (HM) | The combination of human activity and autonomous machine activity, for example |

| | |
|---|---|
| | uploading a photo of the poem to the internet with an app on a smartphone device. |
| Human-machine generator constellation (HMC) | The alternating process of generating and processing information by humans and machines in a tandem, for example uploading a photo of the mentioned poem to the internet with a smartphone device which gets processed by an algorithm to generate advertisements for an app on the smartphone of the user who uploaded the photo, which stimulates the user to buy and download the app. |

The following sources of information in the form of agents are now introduced as CPS components accumulating in a CPS.  Each introduced agent shall be engaging in the process of transferring, storing, recovering, and generating information through agency execution. The next sections illustrate this.

### 9.1.7 Agent type functioning as components of a CPS manufacturing system

A machine generator (M) shall describe information autonomously generated by machine activity through sensors and instruments, for example the amount of information generated and stored by a processor unit in a CPS. (M) shall now be defined by a self-referring feedback loop in the form of a reflexive relation, as displayed in Figure 47.

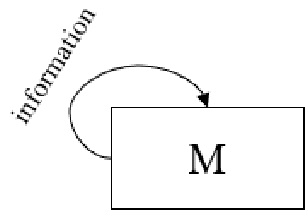



*Figure 47: Machine generator*

Figure 47 shows the alternating process of generating and processing information by machine processors in a tandem positioned in a machine-machine generator constellation (MC). Thus, the combination of information autonomously generated by machine activity through sensors and instruments that processed by another machine, for example the amount of information generated and stored by a set of processor units in a CPS.

(MC) shall now be defined by a graph that contains reflexive and irreflexive relations.

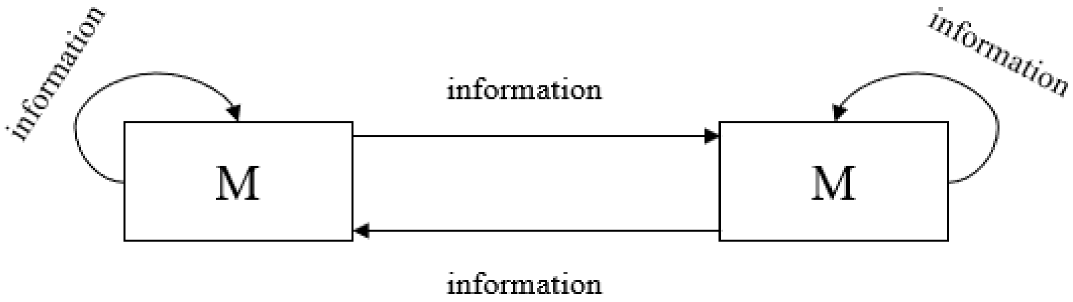



*Figure 48: Machine-Machine Generator constellation*

Figure 49 shows how information is generated by human activities by a human generator (H), for example human learning. (H) shall now be defined as a reflexive relation.

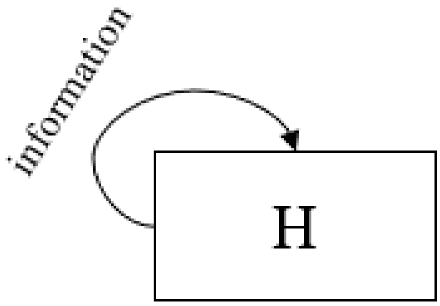



*Figure 49: Human generator*

Figure 50 shows the alternating process of generating and processing information by humans in a tandem by a human-human generator constellation (HHC), for example receiving a message and sending a message back in return.

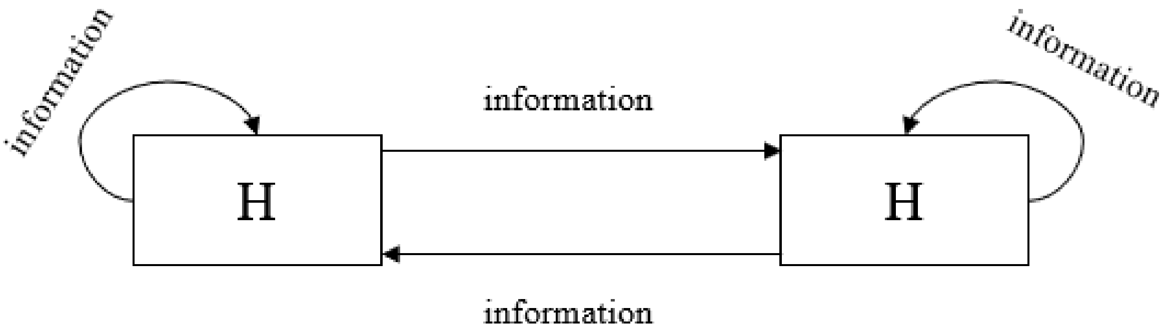



*Figure 50: Human-Human Generator constellation*

Figure 51 shows the alternating process of generating and processing information by humans and machines in a tandem, for example a human acting on a machine processor via an interface in a human-machine constellation (HMC). (HMC) shall now be defined by a graph that contains reflexive and irreflexive relations.

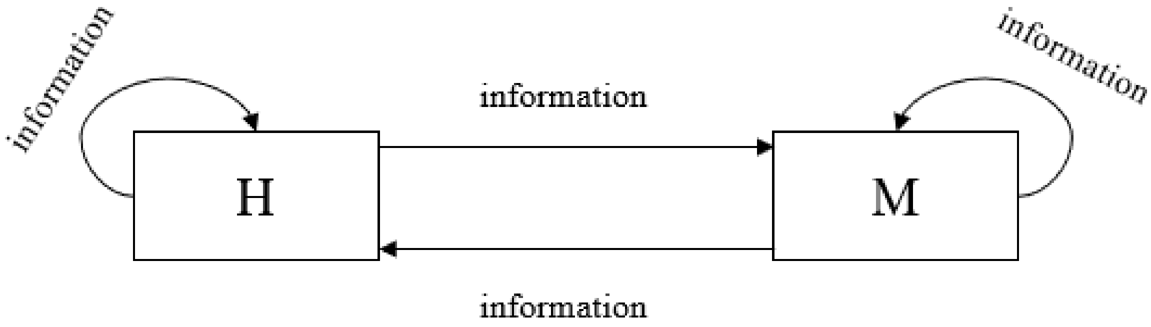



*Figure 51: Human-Machine Generator constellation*

Figure 51 shows that the described sources of information are indicating that different types of agents represent collections of basic functions which can be placed in an interconnected relation in the form of a heterogenous network system where their position and inherent internal irreflexive or reflexive functioning leads to different flows information being created and stored in the system

For this thesis, any of systems that contains at least one machine generator unit (M) shall be named CPS.

Based H1, Hypothesis 2 (H2) now results.

### 9.1.8 Hypothesis 2: Agent based information flow hypothesis

**(H2)** *Any type of information flow in any given industrial information system can be explained by a given combination of sources of information positioned in a network constellation in the form of agents.*

H1 and H2 is now accumulating in the practical context in the concepts of cyber-physical systems (CPS) and is further discussed on the context of information as complexity in CPS in the next section.

### 9.1.9 Information as complexity in CPS

As already established, a CPS can be described as a new generation of complex systems that blend the knowledge of physical artifacts and engineered systems due to integrated computational and physical capabilities.

The provided definitions also make it evident, that a CPS represents a specific network topology with an agent combination that manifests in a practical context of complex economic value creation, for example intelligent manufacturing infrastructure.

Figure 52 now illustrates the basic layout of a completely integrated CPS.

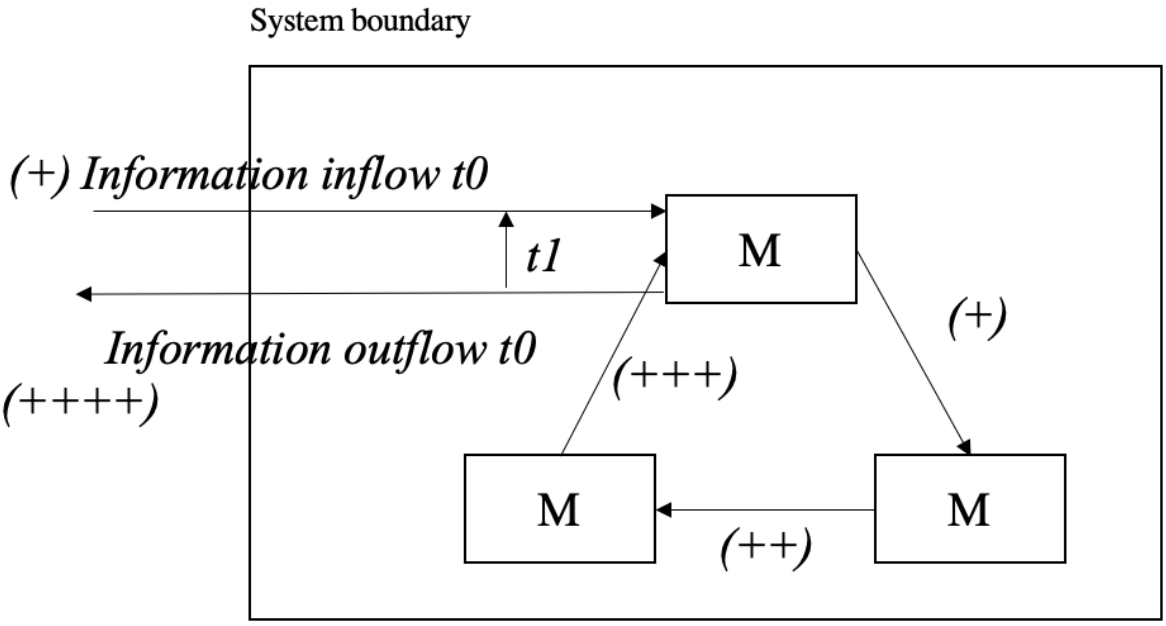



*Figure 52: Integrated CPS with different components*

Figure 52 shows that a CPS can be abstractly described as a network of machine / physical object (M) and data interaction enabled through a rich multi-directional information flow, positioned in a network topology, that increases in contained information over time. (Garcia et al., 2019)

Based on this Figure 53 now provides illustration of how information is assumed to be aggregated over time in such a CPS.

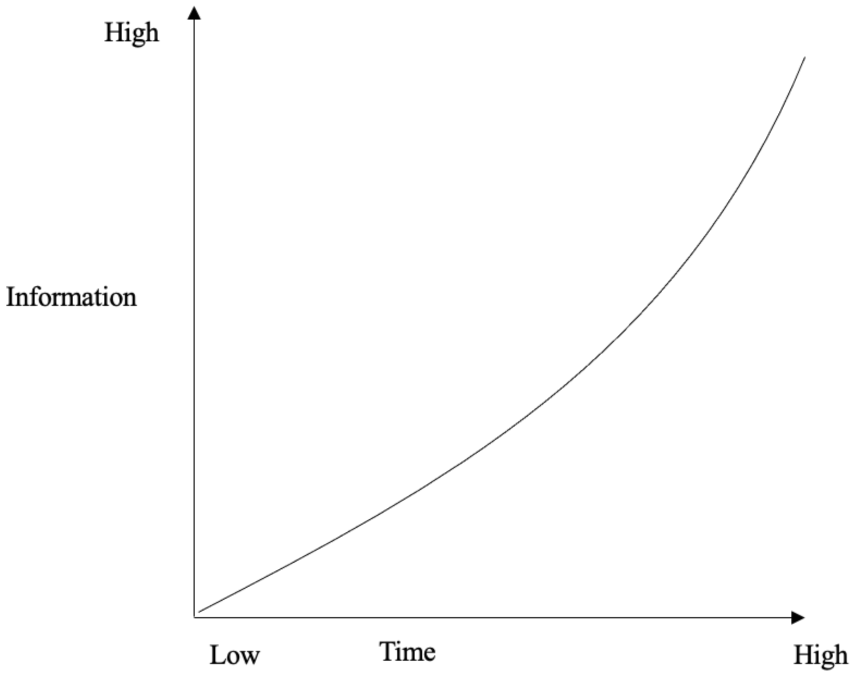



*Figure 53: Information aggregation over time in CPS*

Figure 53 shows, that any type of CPS can be expected to lead to a cascadic growth of circulated information if an undistorted feedback loop is in place. (Jalil & Perc, 2017)

This now allows the introduction of Hypothesis 3 (H3).

### 9.1.10 Hypothesis 3: Cascadic growth of information in industrial information systems hypothesis

**(H3)** *Any type of information flow in a given industrial information system in the form of CPS, CHS can be expected to generate cascadic growth of circulated information if an undistorted feedback loop is in place.*

After presenting hypothesis H3 it is now necessary to provide further information on the concept of increases in generated information through introducing and applying the theory of Shannon Entropy to the notions of H1-H3 to further validate the hypotheses.

### 9.1.11 Shannon entropy

As already shown, it is possible to introduce the idea of a common dominator of complexity by linking the notion of complexity with notion of system entropy. The entropy of a system is in this context regarded as a measure of disorder in the system. Additionally, the concept of energy entropy can directly be linked to the concept of Shannon Entropy, which measures the information content of a message. (Li, 2016, Mourtzis et al., 2019)

This shows that dynamic complexity, when brought into the context of industrial information systems, appears to have a common metric for complexity in the form of energy translated to information under the conception of Shannon Entropy.

The entropy of a system of messages is defined by Shannon as described in equation (2).

$$(2)\ H(X) = -\sum pi(x) log2pi(x)$$

*Where* in this formula pi is the probability of message i in A, which can be identified exactly as the formula for Gibb's entropy in physics. (Mourtzis et al., 2019)

The use of base-2 logarithms ensures that the code length is measured in bits (binary digits). (Mourtzis et al., 2019)

It can now be seen that the communication entropy of a system is maximal, and the predictability is minimal when all the messages have equal probability and thus are typical. (Li, 2016)

The key concept is that of the order of a system, a well-ordered system (message) is simple, therefore non-complex, and vice versa.

The entropy of a system is in this context regarded as a measure of disorder in the form of uncertainty in the system, where a low entropy value implies low uncertainty and vice versa. The higher the disorder, the higher the entropy. If the system is well ordered, it is easy to understand, to predict its behaviour, and to describe and communicate it.

Complexity of CPS shall thus not be regarded as binary state of complex / non-complex but as a degree between total order / certainty and total disorder / uncertainty. (Lent, 2018)

Consequently, Shannon Entropy can be regarded a measure of the information content of data, where information content refers to what the underlying data could contain, as opposed to the more intuitive notion of what it does contain. Therefore, Shannon Entropy is essentially about quantifying predictability or conversely randomness in information. (Mourtzis et al., 2019)

The degree of complexity of a system shall now be determined through Shannon Entropy and therefore by the aggregated amount of information contained in the system with an increase of system complexity resulting from any increase in the amount of information transferred and aggregated in the system and vice versa. (Mourtzis et al., 2019)

The already introduced concept of Shannon Entropy can serve as an explanatory approach to why the amount information contained in a system can serve as a metric for complexity.

The concept of Shannon Entropy can additionally be linked to the context of complex systems through principle of maximum entropy which states that those complex systems tend to maximize entropy production under their present constraints while evolving over time. (Hanel et al., 2014, Jalil & Perc, 2017)

Hypothesis 4 (H4) now results.

### 9.1.12 Hypothesis 4: Complexity of industrial information systems hypothesis

*(H4) The complexity of an industrial information system is defined by the amount of information contained and produced in the system with more information leading to more complexity and vice versa.*

Figure 54 now summarizes the assumptions made in H1-H4.

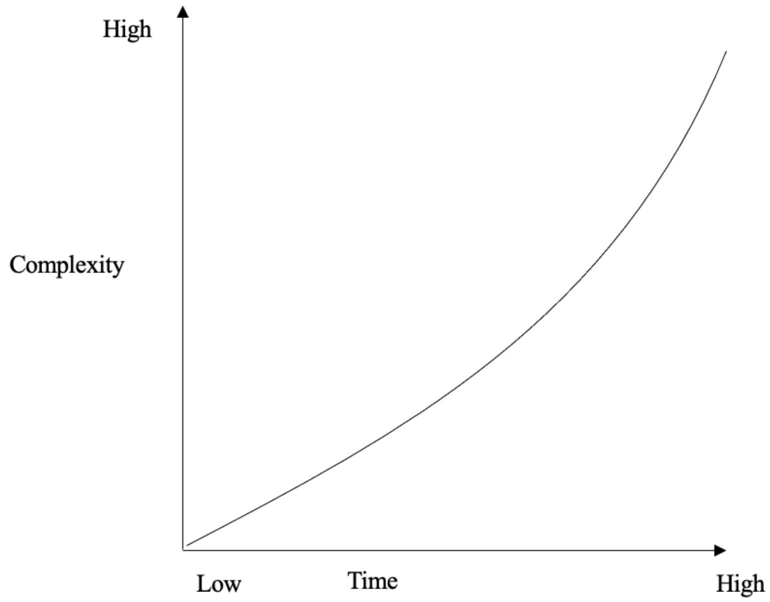



*Figure 54: Hypothetical development of complexity in CPS over time*

Figure 54 shows that a CPS is thus characterized by the characteristics of complexity, volatility, uncertainty and ambiguity (VUCA) as it is characterized by highly interconnected constellation of agent types which lead to an increase of dynamic complexity as defined by Shannon Entropy. (Gimpel & Röglinger, 2015, Mourtzis et al., 2019)

It is therefore shown that it is possible to construct a theoretical connection between the increased implementation of advanced CPS technology, informational growth, and the growth of dynamic system complexity.

The notion of H4 is strongly in line with the research of Wade & Heydari (2014), who propose that system complexity is increasing exponentially over time due to increases in the interconnectivity and the role of human agents in the system.

Based on H1 – H4 it can be theoretically indicated that the amount information aggregated and transferred in a system can serve as an indicator for the development of dynamic system complexity and as a possible explanatory concept for the surges of system complexity in industrial information systems, like CPS.

H1 – H4 now provide the theoretical foundation for further the further exploration of how complexity impacts complex industrial systems like CPS in a system of systems perspective through the discussion of the influence of dynamic complexity on cyber-physical systems of systems (CPSS).

## 9.2 System environment: influence of dynamic complexity on systems of CPS

To underline and to further expand on H1-H4, this section now discusses the development of dynamic complexity in cyber-physical system of systems (CPSS), where CPS components function as information sources in an interconnected network topology based on *Joint Shannon Entropy*.

The Joint Shannon Entropy is now a measure of the uncertainty associated with a set of variables. (Mistry & Banerjee, 2013)

The joint entropy H(X, Y) of a pair of discrete random variables (X, Y) with a joint distribution p(X, Y) is defined as shown in Equation (3).

$$(3)\ H(X,Y) \ = \ H(X) + (H(Y) - I(X,Y))$$

*Where* H(X) and H(Y) are the entropies of the random variables (X, Y) and I(X, Y) is the mutual information both random variables share.

If X and Y are mutually independent then I(X, Y) must be 0 and their joint entropy is equal to the sum of their entropies H(X) and H(Y). If X and Y are not mutually independent their joint entropy will lower than the sum of H(X) and H(Y) since I(X, Y)>0 but greater or equal to the maximum entropy of the individual entities contained.(Mistry & Banerjee, 2013)

The degree of complexity of a CPS shall now be determined through the joint Shannon Entropy of a CPS, H(CPS). For example, a CPS containing two MC components ($MC_1$, $MC_2$) has the joint entropy as displayed in Equation (4).

$$(4)\ H(CPS) = \ H(MC1) + H(MC2) - I(MC1, MC2)$$

*Where* H(CPS)≤ H($MC_1$) +H($MC_2$). H(CPS) now serves as a metric for complexity, entropy and thus, uncertainty of the CPS, with a greater H(CPS) indicating a greater uncertainty and vice versa.

The degree of complexity of a CPSS, H(CPSS), containing two CPS ($CPS_1$, $CPS_2$), shall be determined by the joint entropy as displayed in Equation (5).

$$(5)\ H(CPS1, CPS2) = H(CPS1) + H(CPS2) - I(CPS1, CPS2)$$

*Where* the entropy of all CPS contained in the CPSS, with H(CPSS) ≤ H($CPS_1$) +H($CPS_2$).

Since CPS are defined as a constellation of information sources executing agency in the form of machine and human processor units or constellations and a data pool contained, a CPS itself can be defined as a source of information if the CPS is part of a larger cyber-physical system of systems (CPSS) in which CPS represent the components that exchange and generate mutual and non-mutual information flow in a receptor / processor / effector logic.

Consequently, CPS and CPSS are expected to maximize H(CPS) and H(CPSS) over time if H1-H4 are the case.

This development can be linked to the *Principle of Maximum Entropy* which states that complex systems tend to maximize entropy production under their present constraints while evolving over time. It can also be linked to *Lehman´s Law of increasing complexity*, which states that a systems complexity must increase over time, if the system is not artificially regulated and to the general laws of entropy in a in a system, exemplified in the second law of thermodynamics. (Mistry & Banerjee, 2013, Godfrey & German, 2012, Lent, 2018, Hanel et al., 2014)

If CPS are positioned in a CPSS, information transmission between CPS components is significantly increased and overall system complexity must increase as well.

This is now conceptually illustrated by a scenario where two CPS, as illustrated in Figure 55, are positioned in a closed loop CPSS setup.

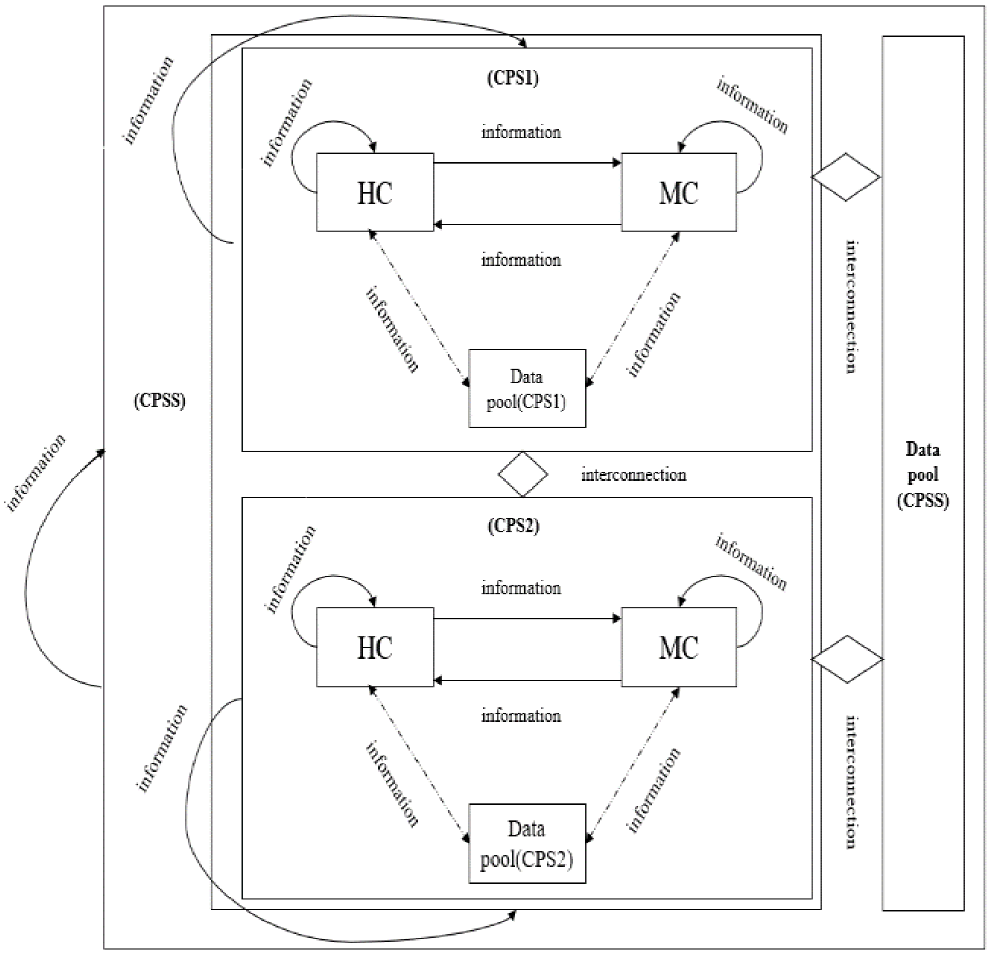



*Figure 55: CPSS example layout*

Figure 55 shows, that the combination of CPS in a CPPS leads to significantly increased information transmission, generation, and storage potential if total interconnectedness is the case since more information sources and data pools are connected.

Figure 56 now illustrates this by showcasing two CPS components of a mechatronics machine which are both physically connected and via a communication network to underline the line of argument. The components of the mechatronics machine interact physically and via information exchange.

The connectivity between components enables direct collaboration among machines with edge or cloud computing resources. Subsystems and components also include machine external computing and communication resources. (Törngren & Sellgren, 2018)

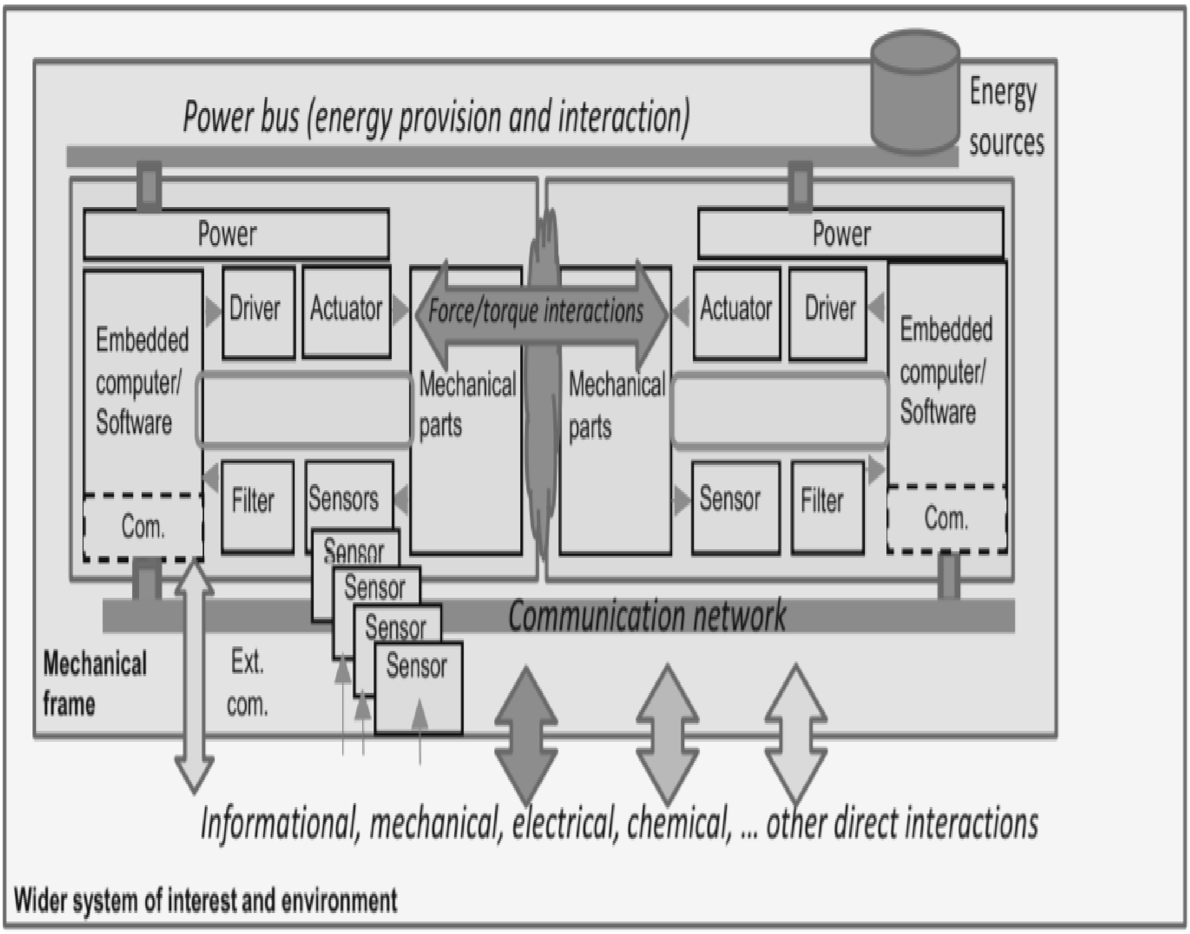



*Figure 56: CPSS of two mechatronic CPS (Törngren& Sellgren, 2018)*

Figure 56 underlines the argument illustrated in Figure 55 and practically exemplifies the high complexity and the extent of multi-dimensional information exchange in current CPSS systems that is even more increased when the CPSS is open loop with enabled environment communication.

Based on H1-H4 and the conception of CPS as sources of information in CPSS and thus sources of entropy H(CPS) which maximize information entropy over time, it is reasonable to define CPS as sources of disorder and uncertainty in CPSS, which maximize joint entropy H(CPSS).

Uncertainty shall now be defined as the situation when the information necessary to obtain to understand and anticipate system developments and changes is insufficient or unavailable leading to decreased system predictability. (Thoma et al., 2020)

Complexity in this context can furthermore be defined as the measure of uncertainty that a system can satisfy the functionality of the system. (Blecker & Abdelkafi, 2006)

System functionality shall be defined as a low or non-existing probability of occurrence of undesired events and thus of a low overall system risk. (Törgren & Grogan, 2018)

As a first conclusion and as shown in Freund & Al-Majeed (2020a) the impact of dynamic complexity on cyber-physical systems is illustrated in Figure 57.

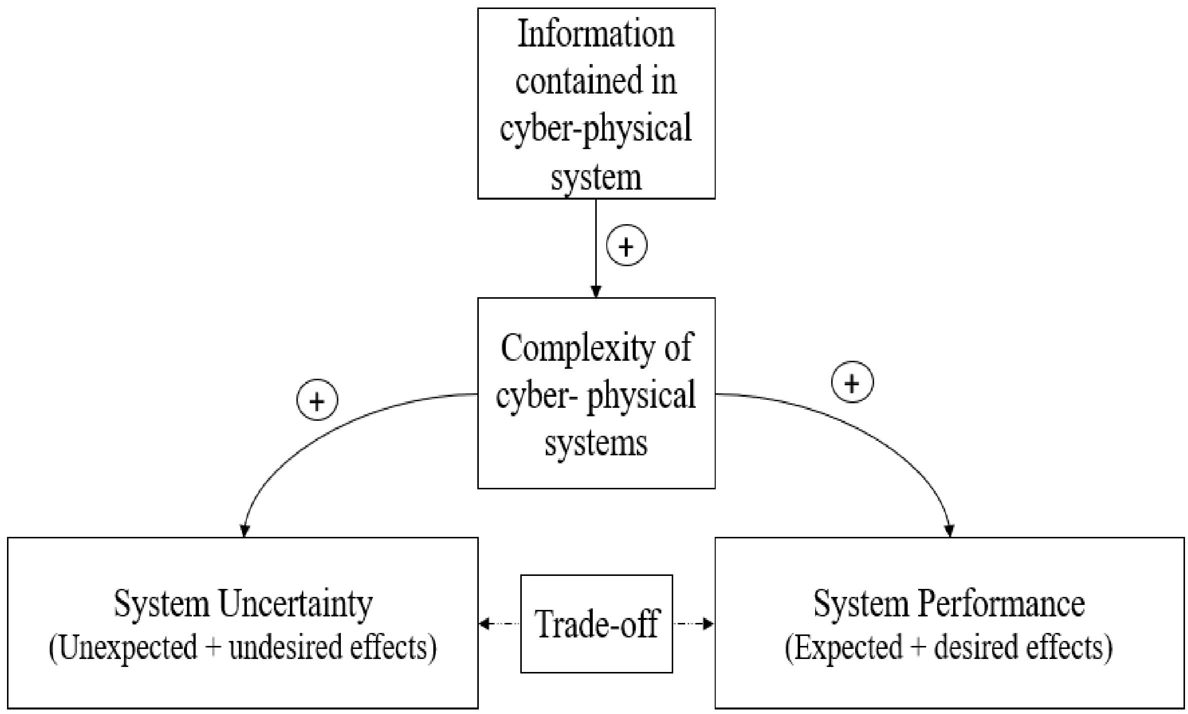



*Figure 57: Impact of dynamic complexity on CPS(S) (Freund & Al-Majeed, 2020a)*

It can consequently be shown that an increase in system complexity is expected to lead to a decrease of system functionality in the form of an increase in unpredictability and an increase of system risk, represented through the occurrence of undesired events in the system lifecycle.

At the same time a trade-off relationship exists with an increase in system functionality in the form system performance as an increase in dynamic complexity enables more functionality in the CPS and potentially allows the creation of more expected and desired events.

Therefore, CPS function as both sources of increased system risk and increased system performance at the same time in CPSS, leading up to a trade-off relationship between both aspects, which must be considered when designing CPSS architectures. (Törngren & Sellgren, 2018)

The established trade-off relationship shows that CPS and CPSS can be regarded as effective technologies to increase system performance with higher output where the impact of dynamic complexity can lead to decreased system efficiency, as potential benefits are possibly accompanied by high system input cost to assure system stability.

It is shown that CPS itself can be expected to maximize entropy for themselves and for the CPSS they are positioned in over time if not artificially regulated. It can thus be theoretically indicated that the amount of information aggregated and transferred in a CPS can serve as an indicator for the development of dynamic system complexity in both the system itself and any CPSS it is positioned in.

It can thus serve as an indicator for the implications of increased dynamic system complexity in CPS and CPSS like increased system risk through system uncertainty.

It is shown that the increase of effectiveness through the introduction of a CPSS architecture is accompanied by a decrease of overall system efficiency, since dynamic complexity increases. Consequently, the importance of developing appropriate, cost-efficient risk management and control systems for CPS and CPSS must be highlighted to achieve effective, efficient, and safe deployment for system stakeholders by decision makers.

It furthermore allows the line of argument, that complex systems management leads to a quasi-paradoxical situation: The decision to implement complex systems to achieve higher performance leads to a at least proportionate cost of system uncertainty and risk which might mitigate the performance increases achieved.

This paradox shall be named the *"complex system performance / risk trade-off"*.

The meaning of this paradox for decision-makers is now further explored in the next chapter in the context of the dimension of decision-making and system regulation.

## 9.3 Decision-making: influence of dynamic complexity on decision making and system regulation

After defining the concepts of information and complexity in industrial system in H1-H4 and the introduction of the “complex system performance / risk trade-off” it is now possible to introduce further theoretical assumptions in the form of additional voluntary hypotheses concerning the subjective, epistemological nature of complexity via system regulation as the strategic act of a decision-maker intervening in a system´s dynamics.

### 9.3.1 System regulation

The core function of system regulation (SR) in a complex industrial system shall be defined as a direct reduction of system disturbance (D) to keep the goal of the system intact.

A regulator / decision-maker of system thus imposes a set (R) of regulatory responses on a set (D) of system disturbances.

Disturbance (D) shall be defined in proportion to information complexity and consequently as an expression of joint system Shannon Entropy H(P). Consequently, the act of system regulation can be broadly defined as a function (f) of regulatory responses (R) and system disturbances (D), as shown in Equation (6).

$$(6)\ SR = f(R, D)$$

The central goal of a system regulator shall thus be to reduce the flow of information in the system against a set of disturbances by systematically intervening in the systems dynamics. (Schuck, 2019)

Figure 58 now illustrates this process.

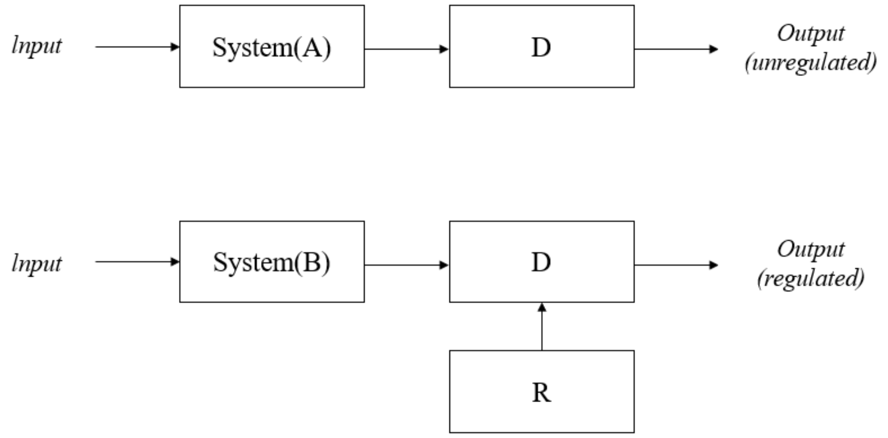



*Figure 58: Basic process of system regulation*

Based on Figure 58, the basic function of regulation can be illustrated by considering two models of temperature records of a set of two water pools (A, B) exposed to the same environment conditions, which shall be regulated to a constant temperature by a heater.

Figure 59 illustrates this.

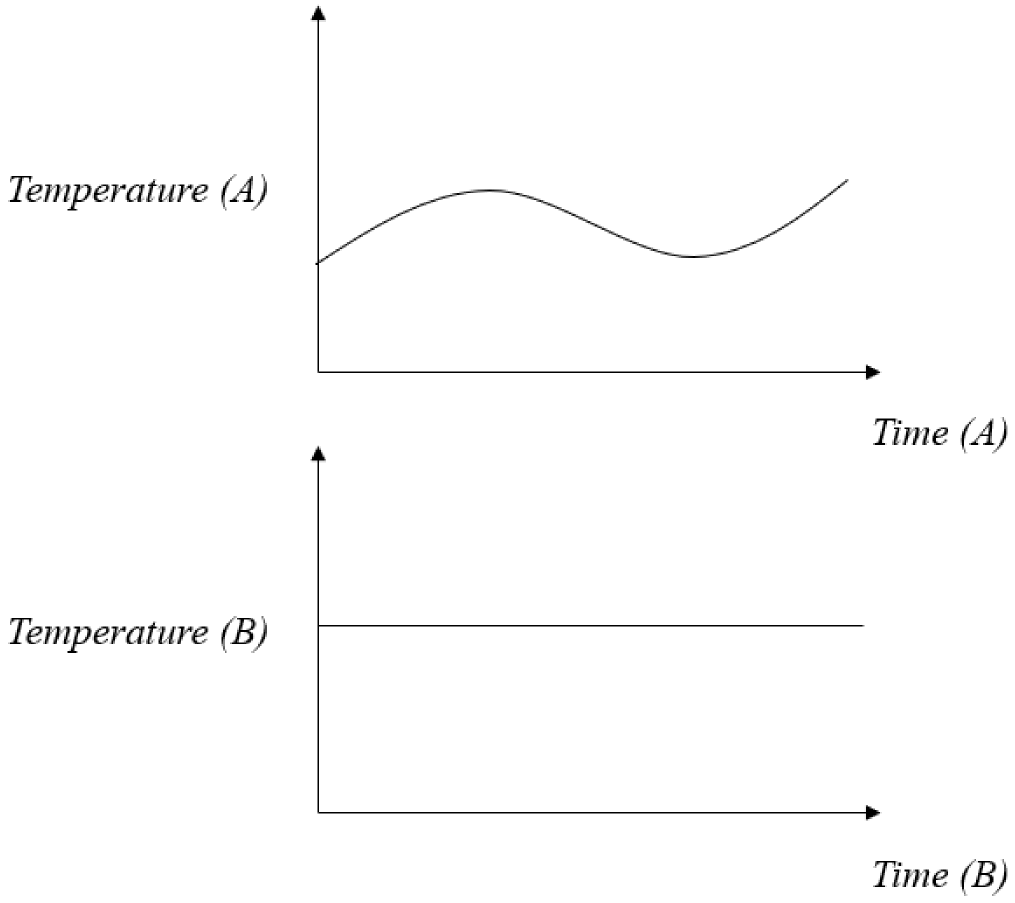



*Figure 59: Regulation of two water pools*

The provided example shows that water pool B is better regulated as no information about any disturbances induced by environment temperature changes can be identified and no deviations from the desired temperature took place.

Consequently, regulation (SR) blocks the flow of variety and therefore provides the control of influence. The perfect thermostat would be one that, despite a disturbance, kept the temperature constant at the desired level. (Schuck, 2019)

Based on these thoughts the next chapter now provides an approach to model the relationship of disturbance and regulation in an industrial system.

### 9.3.2 A model of disturbance and regulation in complex systems

An industrial system ($S_n$) with a given complexity defined as static and dynamic complexity and the resulting disturbance set ($D(S_n)$) shall be met by a set ($R(S_n)$) of regulatory responses where R [r1…rn]. (Ashby, 1991) A regulatory response might be any counter measure that can be undertaken as a reaction to a system disturbance by a rational decision-maker.

Figure 60 illustrates this.

| D / R | r1 r2 r3 r4 …. |
|---|---|
| d1<br>d2<br>d3<br>d4<br>… | |

*Figure 60: Disturbance set with regulatory response set*

Consequently, it can be stated that a maximization of system disturbances leads to a maximization of the regulatory response set.

Equation (7) describes this.

$$(7)\ \mathrm{D}(S_n)_{max} = R(S_n)_{max}$$

*Where* $\mathrm{D}(S_n)_{max}$ = maximum system disturbances and $R(S_n)_{max}$ = maximum regulatory responses.

Based on Equation (7), Hypothesis 5 can now be derived.

### 9.3.3 Hypothesis 5: Disturbance and regulatory response proportionality hypotheses

*If a system maximizes its set of system disturbances, the set of regulatory responses must also be maximized.*

### 9.3.4 Regulation & Outcome

Based on the Hypothesis 5, it is now possible to attribute to every disturbance / regulatory response combination a given outcome set Z with [z11…zij].

Figure 61 now introduces the outcome matrix of a given disturbance and regulatory response set. (Ashby, 1991)

| D / R | r1 r2 r3 r4 …. |
|---|---|
| d1 | z11 z12 z13 z14 … |
| d2 | z21 z22 z23 z24 … |
| d3 | z31 z32 z33 z34 … |
| d4 | z41 z42 z43 z44 … |
| … | … … … … … |

*Figure 61: Outcome matrix*

The displayed outcomes shall furthermore not be attributed with any kind of desirability for the decision maker and only map the product set D x R into the set Z of possible events in the form of outcomes.

Consequently, it can be stated that a maximization of system disturbances leads to a maximization of the outcome set.

Equation (8) describes this.

$$(8)\ \mathrm{D}(S_n)_{max} = Z(S_n)_{max}$$

*Where* $\mathrm{D}(S_n)_{max}$ = maximum system disturbances and $Z(S_n)_{max}$ = maximum possible outcomes.

Based on Equation (8) Hypothesis 6 can now be derived.

### 9.3.5 Hypothesis 6: Disturbance and system outcome proportionality hypotheses

*If a system maximizes its set of system disturbances, the set of possible outcomes must also be maximized.*

The Hypotheses 5 and 6 can now summarized by the effect diagram displayed in Figure 62.

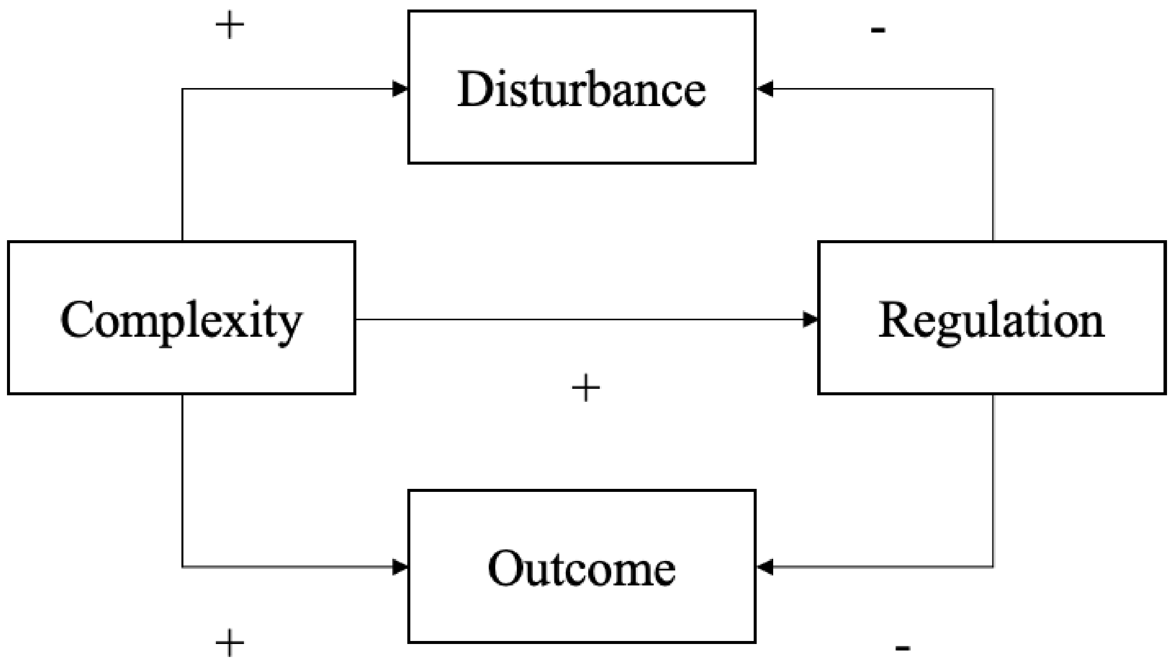



*Figure 62: The relationship of disturbance, regulation, and outcome*

Figure 62 shows, that the extent of the regulation is directly dependent on the extent of disturbances in a system, while the extent of outcomes in dependent on the extent of regulation and disturbance.

This allows to extent the function proposed in Equation (8) to the Equation (9):

$$(9)\ SR = f(R, D, O)$$

Equation (9) shows that system regulation (SR) now can be defined as the function of regulatory response (R), disturbance (D) and the outcome (O).

After introducing the concepts of the disturbance, regulatory response, and outcome set, as well as H5 and H6 it is now possible to explore how the decision-making process of a rational decision-maker functioning as the system regulator can be modelled under the given assumptions.

### 9.3.6 Rational decision making and complex system regulation

When describing the process of decision-making in complex industrial systems, it is necessary to define the assumed modus operandi of the individual´s decision making process if situated in a decision problem.

This is achieved in the form of the *standard theory of rational choice* and assumptions concerning the nature of rational decisions made under uncertainty and under risk. A decision problem in this case shall be defined as the act of defining the most optimal, utility maximizing function of (SR) for a given system in each managerial situation and its parameters.

To allow the creation of a model to demonstrate how the decision-making in a complex industrial system can function, the assumptions of the standard theory of rational choice (SRC) are now introduced.

SRC assumes that individuals do not act randomly, but follow a more consistent approach, a strategy, while making decisions. They therefore exercise instruments of rational choice, while aiming to achieve an optimized outcome.

It shall now be assumed that rational agents are the starting point of every action, that these rational agents are provided with usable resources. They exercise preferences and can choose between at least two options and that agents act according to a coherent decision rule that can predict how the agent chooses. (Bradley, 2014, Diekmann, 2004)

This indicates that the standard definition of rational choice describes a consistent approach to define individual thinking to maximize a certain outcome in a certain scenario of choices. It is therefore based on the assumption, that individuals have preferences and act according to these preferences and therefore are exercising an optimization-based approach. (Levin & Milgrom, 2004)

Agent preferences are expressed through preference relations, meaning that an individual either strictly prefers x to y, with $x>y$, or is indifferent between x and y, with $x \sim y$. All preferences combined result in a choice set (X) of the rational agent. (Levin & Milgrom, 2004, Bradley, 2014, Straub & Welpe, 2014)

Furthermore, it is assumed in this instance that the individual chooses under certainty, therefore attributing a probability of $p=1$ to every preference. In the context of a rational agent positioned in an industrial system outcome matrix, the choice set (X), with [x1…xn] with $x \in X$, of the rational agent equals the response set (R), with [r1…rn] for the given system, resulting in $r \in X$. Consequently, an increase in (R) must lead to an increase in (X) and vice versa.

Hypotheses 7 and 8 can now be derived.

### 9.3.7 Hypothesis 7: Choice set hypothesis

*The choice set of a rational decision-maker in the role of a system regulator is equal to the set of regulatory responses.*

### 9.3.8 Hypothesis 8: Choice set maximization hypothesis

*If a system maximizes its set of disturbances, the resulting choice set of a regulating decision-maker is also maximized.*

If the assumptions of SRC are met, the described rational agent is at any time capable to choose the preferred preference from the underlying choice set. (Levin & Milgrom, 2004)

Therefore, a metric for desirability ($\partial$) can be attributed to every outcome ($z_{ij}$) in an outcome set (Z) of a given system.

To illustrate this, Figure 63 shows an exemplary outcome matrix with D[d1…d4], R[r1…r4] in which every disturbance / response combination results in either a preferred outcome or a non-preferred outcome for the deciding agent.

A preferred outcome shall be noted as the binary notions of (1) and the non-preferred outcome shall be noted as (0), with the attributed preferences based on the assumption that a rational agent prefers any solution to a system disturbance set over no solution at all times.

| D / R | r1 | r2 | r3 | r4 |
|---|---|---|---|---|
| d1 | 1 | 0 | 1 | 0 |
| d2 | 1 | 0 | 1 | 0 |
| d3 | 0 | 0 | 1 | 0 |
| d4 | 1 | 0 | 1 | 1 |

*Figure 63: Outcome matrix with preferences*

Figure 63 shows that an outcome matrix of a complex industrial system represents a decision situation in which a rational agent has the choice set (X)=(R), with [r1…r4]. Based on the assigned preference values in the shown example the rational agent has the following preference relation: r3>r1>r4>r2.

Consequently, the rational agent chooses response r3 in the given scenario to maximize preferences and the overall outcome, by deciding for the most optimal counter measure against system disturbance.

Based on Figure 68, Equation (9) can now be modified to Equation (10) which includes desirability ($\partial$) in the defined function.

$$(10) \qquad \mathrm{SR} = \mathrm{f}(\mathrm{R}, \mathrm{D}, \mathrm{O}, \partial)$$

Applying the standard theory of rational choice to model strategic individual decision-making behaviour in a scenario of complex industrial system allows to normatively model the acting individuals as rational agents driven by clearly defined preference relations in a clearly defined choice set.

The application of mathematics to increase the deductive and predictive capability of the model and to obtain an overall understanding of the decision problem is furthermore enhanced through the introduction of the concept of utility. (Levin & Milgrom, 2004, Diekmann, 2004)

### 9.3.9 Utility functions

The concept of utility assumes, that if an agent has complete and transitive preferences then preferences can be associated with a utility function. (Board, 2009) The existence of a utility function (u(x)) ranks and represents an individual´s preferences by equipping each preference with a certain number of utilities.

A utility function associates different numbers to different preferences, and have the agent choose the preference with the highest number. These numbers are called utilities. In turn, a utility function tells the utility associated with each preference $x \in X$ and is denoted by $u(x) \in$ <. (Bradley, 2014, Levin & Milgrom, 2004, Diekmann, 2004, Board, 2009)

Equation (11) illustrates this.

$$\text{(11)} \qquad \mathrm{u}(\mathrm{x}) \geq \mathrm{u}(\mathrm{y}), \text{if and only if } \mathrm{x} < \mathrm{y}$$

This means than an agent makes the same choices whether it is based on the preference relation, <, or the utility function u(x).

Consequently, if the attributed values (1) and (0) for preferability and non-preferability displayed in Figure 63 are assumed to be utility, the resulting utility function for the rational agent would be u(r3=4, r1=3, r4=1, r2=0) resulting in u(r3,r1,r4,r2) and therefore in a utility function consistent with the underlying preference relation r3>r1>r4>r2 that maximizes both utility and preferences of the rational system regulator.

To make the model more realistic, the next section now investigates decisions under uncertainty by introducing Von Neumann-Morgenstern utility functions.

### 9.3.10 Decisions under uncertainty: Von Neumann-Morgenstern utility functions

Up until this point, SRC was assumed and therefore the rational agent expected to decide under the condition of being fully informed about all possible outcomes of the R x D decision matrix. Consequently, the rational agent maximizes utility under the assumption of outcome certainty and complete information about all R x D combinations and resulting outcomes O.

To achieve a more nuanced model of rational behaviour, the concept of uncertainty can be introduced to the decision matrix by utilizing the concept of expected utility.

Uncertainty shall be defined as a state of a lack of information and therefore can be defined as the decision-maker making decisions based on incomplete knowledge about the outcomes that result from a disturbance / regulation combination.

This shall be modelled by the addition of a probability set to the outcomes of an outcome matrix and thus in the form of an expected utility function. (Kurhade & Wankhade, 2016, Briggs, 2019, Straub & Welpe, 2014)

To do this the basic principle of utility theory developed by Von Neumann-Morgenstern is applied.

Utility is assigned to the attributes in such a way that a decision (on which action to take) is preferred over another if, and only if, the expected utility of the former is larger than the expected utility of the latter. (Bradley, 2014)

The resulting expected utility of a decision (A) by rational agent shall be defined as described in equation (12).

$$\text{(12)} \qquad \mathrm{EU(A)} = \sum_{\mathrm{o} \in \mathrm{O}} \mathrm{PA(o)U(o)}$$

*where* O is the set of outcomes, PA(o) is the probability of outcome o conditional on A, and U(o) is the utility of o. The term PA(o) represents the probability of o given A and thus how likely it is that outcome o will occur, on the supposition that the agent chooses act A. (Briggs, 2019)

Decision making based on the expected utility theory therefore requires decision-makers to assess the probability of all relevant system outcomes, thus increasing the extent of necessary information to be obtained by the decision-maker.

The assigned probabilities therefore represent the knowledge in the form of information about the system of the decision maker at the time of making the decision. (Briggs, 2019, Straub & Welpe, 2014)

Figure 64 now integrates the concept of expected utility into the presented outcome matrix by attributing a probability (pn), with (p1+p2+pn=1) to every outcome (zij).

| D / R | r1 | r2 | r3 | r4 …. |
|---|---|---|---|---|
| d1 | z11(p1) | z12(p2) | z13(p3) | z14(p4) … |
| d2 | z21(p1) | z22(p2) | z23(p3) | z24(p4) … |
| d3 | z31(p1) | z32(p2) | z33(p3) | z34(p4) … |
| d4 | z41(p1) | z42(p2) | z43(p3) | z44(p4) … |
| | … | … | … | … … |

*Figure 64: Outcome matrix with uncertain outcomes*

Consequently, the utility function of a rational regulating decision maker can be described by the expected utility form, in the form of a Von Neumann-Morgenstern utility function as shown in equation (13).

$$\text{(13)} \qquad U(p) = \sum_{i=1}^{n} p_i \times u_i$$

*Where* there are numbers (u1, ..., un) for each of the O outcomes (z11, ..., zij) for every p ∈ P. (Briggs, 2019)

Based on this, Hypothesis 9 and 10 can now be derived.

### 9.3.11 Hypothesis 9: Required information hypothesis

*If a system maximizes its set of disturbances, the necessary knowledge in form of information about the system a decision-maker must have to attribute objective probabilities is also maximized.*

### 9.3.12 Hypothesis 10: Uncertainty maximization hypothesis

*If a system maximizes its set of disturbances, the resulting uncertainty in a choice set of a regulating decision-maker is also maximized.*

Hypotheses 9 and 10 are additionally supported by the *Law of requisite variety*, which states that a decrease of disturbance and outcome variety must always be accompanied by a proportional increase in regulation variety.

For example, if a disturbance set introduces a variety of 10 bits for outcomes and only a variety of 5 bits shall be acceptable, the variety of regulation must at least encompass a variety of 5 bits. (Ashby, 1991)

This notion is further expanded on by Shannon communication theory which states that if noise appears in a message, the amount of noise that can be removed by a correction channel is limited to the amount of information that can be carried by that channel.

As a next step, decisions under risk are now integrated into the model.

### 9.3.13 Decisions under Risk

Since uncertainty can be attributed with risk, a situation where the decision-maker is unsure which outcome might occur because of the decisions made shall be defined as a decision situation under risk. (Kurhade & Wankhade, 2016, Briggs, 2019)

The term risk shall therefore be defined as the expected change in utility associated with uncertain, undesirable outcomes. (Straub & Welpe, 2014)

The word "risk" shall furthermore be comprised of the following two elements:

- The probability (or likelihood) of occurrence of a negative event during the lifetime of a system.
- The resultant consequence when a negative event has taken place.

The objective of regulation is now to conduct an assessment to bode negative effects so that adverse outcome can be minimized.

Consequently, the risk of a decision-maker contained in the act of system regulation (SR) can be associated with unexpected changes in utility as shown in equation the following Equation (14):

$$\text{(14)} \qquad \mathrm{EU(r)} = \mathrm{u}\left(\mathrm{z_{ij} x\, p_{ij}}\right) + \mathrm{u}(-\mathrm{az_{ij}\ x\ 1 -\ \ p_{ij}})$$

*Where* $\mathrm{EU(r)}$ = expected utility for a regulation r, $\mathrm{u}\left(\mathrm{z_{ij} x\, p_{ij}}\right)$ = expected utility of desirable outcome, $\mathrm{u}(-\mathrm{az_{ij}\ x\ 1 -\ \ p_{ij}})$=expected utility of undesirable, deviating outcome.

Based on Equation (9) the final hypothesis of this paper can now be derived.

### 9.3.14 Hypothesis 11: Risk maximization hypothesis

*If a system maximizes its set of disturbances, the risk contained in a choice set of a decision-maker is also maximized.*

Based on these thoughts Equation (14) can now be modified through the addition of an undesirable outcome (-$\partial$) to the following function displayed in Equation (15).

$$\text{(15)} \qquad \mathrm{SR} = \mathrm{f}(\mathrm{R}, \mathrm{D}, \mathrm{O}, \partial, -\partial)$$

Equation (14) can now be regarded as the central conclusion to this section.

It is shown that it is possible to hypothesize in the form of H5 to H11 that the act of system regulation is highly dependent on the underlying information complexity und corresponding disturbance set of the system.

A growth of system complexity thus leads for the rational decision maker to a proportional increase in choice risk and choice uncertainty, leading to up to an increasingly difficult decision-making process.

H5 – H11 now show that complex industrial systems like CPS involve an increasingly difficult decision-making process and as complexity of the system increases the strategic capabilities of the decision-maker must decline.

Consequently, the proposed “complex system performance / risk trade-off” is additionally supported through the hypotheses developed.

To formulate an answer to the identified dynamics the next section now provides an argument why heuristics are important to complex systems management, based on cybernetics theory to further support and further expand the hypotheses introduced in the dimension of decision-making.

## 9.4 Heuristics in the context of cybernetics and systems management

To further expand on the hypotheses H5-H11 and on the "complex system performance / risk trade-off*"* introduced and defined in the last chapters, an advanced argument for the necessity of heuristics in the management of complex systems based on cybernetics theory is proposed. The cybernetician Ashby (1991) researched the variety of situations that a machine could respond to and adapt to while exploring the field of cybernetics, the science of control and communication in animals and machines.

### 9.4.1 Cybernetics

Cybernetics is based on the idea that all living, and most mechanical systems are sustained by the presence of positive and negative feedback loops; the first amplifying and the second dampening information bearing signals of relevance to them. The study of negative feedback in general systems theory showed how systems act to preserve themselves under changing external conditions.

The distinction between the system's interior and its exterior is essential to the preservation of a system's identity and continued survival under conditions of environmental change. Through the mechanism of homeostasis, a system can maintain an internal equilibrium in the face of external perturbations. (Ashby, 1991),

Systems are also capable of generating change autonomously by amplifying feedback instead of merely adapting to external contingencies by dampening it. (Boisot & McKelvey, 2011)

### 9.4.2 The law of requisite variety

In this context Ashby introduced the *Law of Requisite Variety* (Ashby´s Law) which states that "only variety can destroy variety":

*"(...) a system survives to the extent that the range of responses it is able to marshal – as it attempts to adapt to imposing tensions – successfully matches the range of situations – threats and opportunities – confronting it."* (Ashby, 1991)

Based on Ashby´s Law it can now be concluded that to not to waste energy responding to every possible internal or external fluctuation, a system must build schemas in ways that distinguish meaningful information from noise. In the context of strategic complexity management, it must be distinguished between what Gell-Mann has labelled 'effective', meaningful, and 'crude', noise, complexity. (Schuck, 2019, Boisot & McKelvey, 2011, Coleman 1994) Based on

Ashby´s Law it is possible to introduce the *Conant-Ashby Theorem*, which states that every good regulator of a system must be a model of that system. In other words, the result of an organizational process cannot be better than the model on which the management of that process is based, except by chance. This thus indicates the high relevancy of appropriate management models and strongly supports the hypotheses introduced. (Schwaninger, 2000)

Boisot & McKelvey (2011) state that it must be noted that what constitutes information or noise for a system is partly a function of the system's target function and that it can be inferred that valid and timely representations of a system in the form of decision-making models must economize a system´s limited energy resources.

### 9.4.3 Ashby Space

To illustrate the functioning of Ashby´s law it is possible to introduce Boisot & McKelvey´s concept of Ashby space. Ashby space is now illustrated in Figure 65.

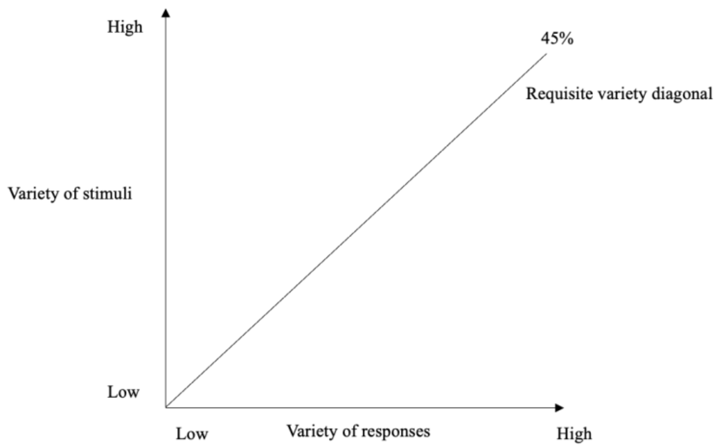



*Figure 65: Ashby space*

On the vertical axis the real-world stimuli that impinge on a system are placed. These range in variety from low to high. On the horizontal axis, the variety of a system's responses to the stimuli are placed. These also range from low to high.

The diagonal in the diagram indicates the set of points at which variety can be considered "requisite", where the variety of a system's response matches that of incoming stimuli in an adaptive way. It is keeping a system´s target function intact, whether or not it does so with an efficient use of resources. The concept of Ashby space can now be used to introduce the concept of an adaptive frontier to allow interpretation in the context of strategic complexity management. (Boisot & McKelvey, 2011)

### 9.4.4 The adaptive frontier

Figure 66 describes a response or resource budget available to a system defined in terms of energetic, temporal, and spatial resources.

The curve constitutes the system's adaptive frontier, the region in which it reaches the limit of the budget it can draw on for the purposes of adaptation.

To the right of this region, the mix of variety required to respond to incoming stimuli is too high for adaptive purposes, causing the system to spend too much of its resource budget and eventually leading to its disintegration.

Furthermore, the resources consumed by the data processing required to register incoming stimuli, to interpret them, and to formulate adaptive responses also exceed the system's resource budget, eventually leading to errors and to adaptive failure. (Boisot & McKelvey, 2011)

This is illustrated by Figure 66.

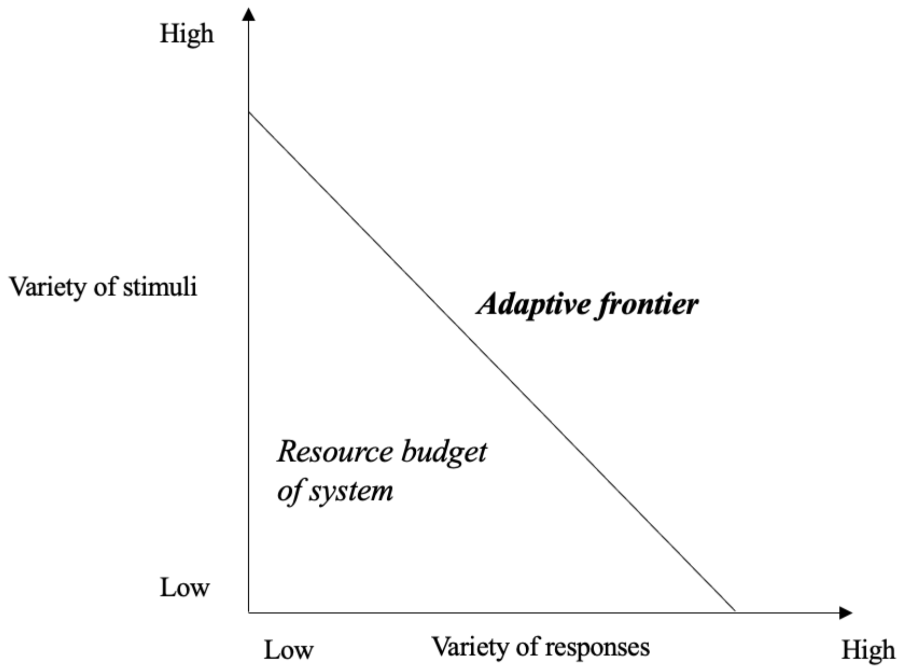



*Figure 66: Adaptive frontier*

Under the assumption of the already introduced and discussed U-shaped performance / effort relationship and the underlying "complex system performance / risk trade-off" and a restricted resource budget, it is possible to re-introduce the line of argument that optimization models appear to be not well suited to work efficiently under realistic complex system conditions.

The premise of highest importance for this argument is the premise of a limited resource budget of system in relation to its adaptive frontier.

Figure 67 illustrates the impact of heuristics on the adaptive frontier of a given system.

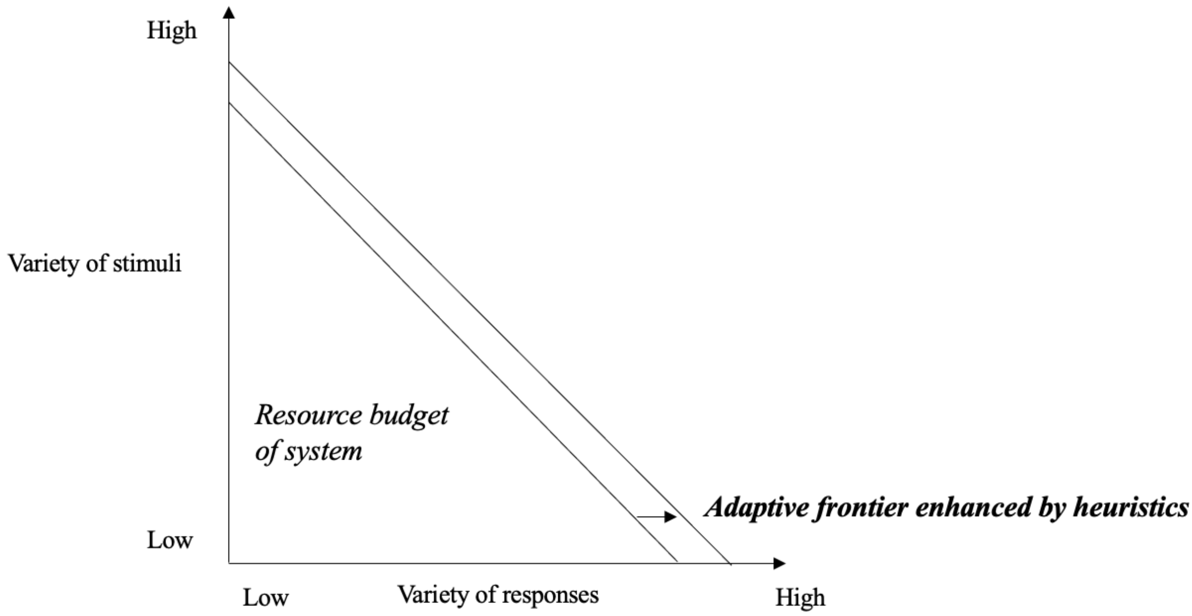



*Figure 67: Adaptive frontier enhanced by heuristics*

Figure 67 shows that the goal of heuristics can be translated in the context of Ashby space and the adaptive frontier to increasing the resource budget of the system and thus leading to a higher variety of responses and a higher variety of stimuli the system can withstand before it reaches disintegration.

Due to the less-is more effect of heuristics the overall risk of reaching the adaptive frontier through resource budget utilization is effectively minimized.

In the case of resource intensive optimization models, it can be argued, that they exploit the resource budget of a system in an intensive fashion, thus risking system disintegration of they not effectively enhance the adaptive frontier of the system.

Based on the statements made the next section now further expands on the relationship between system complexity and system assessment type performance.

## 9.5 The relationship between system complexity and system assessment type performance

The relationship between system complexity and system assessment performance in relation to heuristic and optimization methods is illustrated in Figure 68.

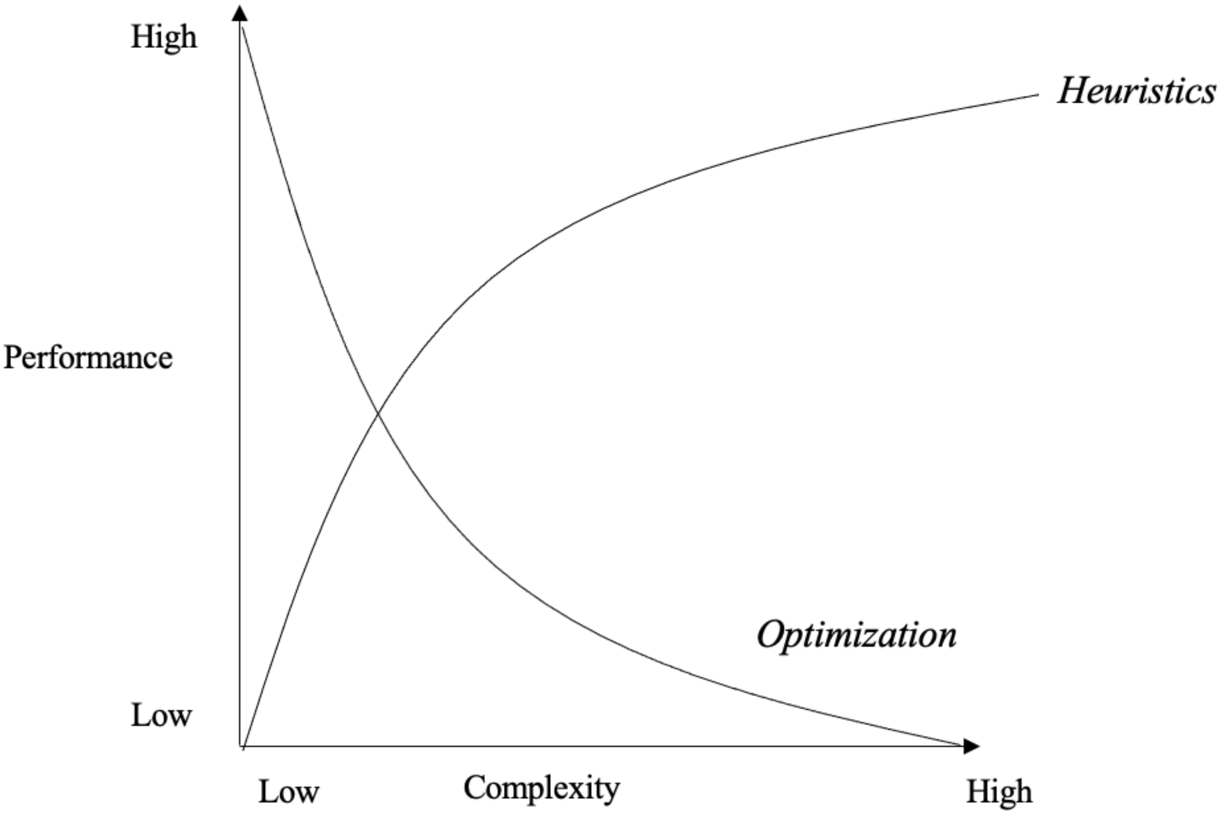



*Figure 68: Relationship system complexity and assessment type performance*

Figure 68 shows, that in the context of complexity the relationship of heuristics and optimization methods is to be regarded as of an inverted nature.

In low complexity system optimization methods are resulting in a higher performance and in an increasingly complex system their performance deteriorates.

In contrast heuristics perform increasingly well in a high complexity environment, while their performance might not be as high as optimization methods in a low complexity environment.

Consequently, H12 and H13 shall be established for this thesis.

### 9.5.1 Hypothesis 12: positive heuristics effect hypothesis

*If a system maximizes its set of disturbances, the risk contained in a choice set of a decision-maker can be minimized through the application of heuristics models.*

### 9.5.2 Hypothesis 13: negative optimization effect hypothesis

*If a system maximizes its set of disturbances, the risk contained in a choice set of a decision-maker can be maximized through the application of optimization models.*

The provided results of this part of the thesis allow to draw the following implications for the coming parts of this study.

Considering the established hypotheses H1-H13 it can thus be shown that humans present both the source of and means to impact the balance of complexity positively by mitigating the negative downsides in the form of increased system disturbance, outcome and regulation sets with improved new knowledge and heuristic tools via exercising strategic complexity management.

As defined in the paradigm of strategic complexity engineering and as postulated by Törngren & Grogan (2018) knowledge in the form of hypotheses establishes explanatory links between complexity phenomena and help improve anticipation of the engineering problem and perception of negative downsides.

In this regard, tools help humans to focus efforts at higher levels of abstraction, execute strategy and in the best-case scenario, to optimally solve well-characterized complexity decision-making problems.

Figure 69 illustrates this.

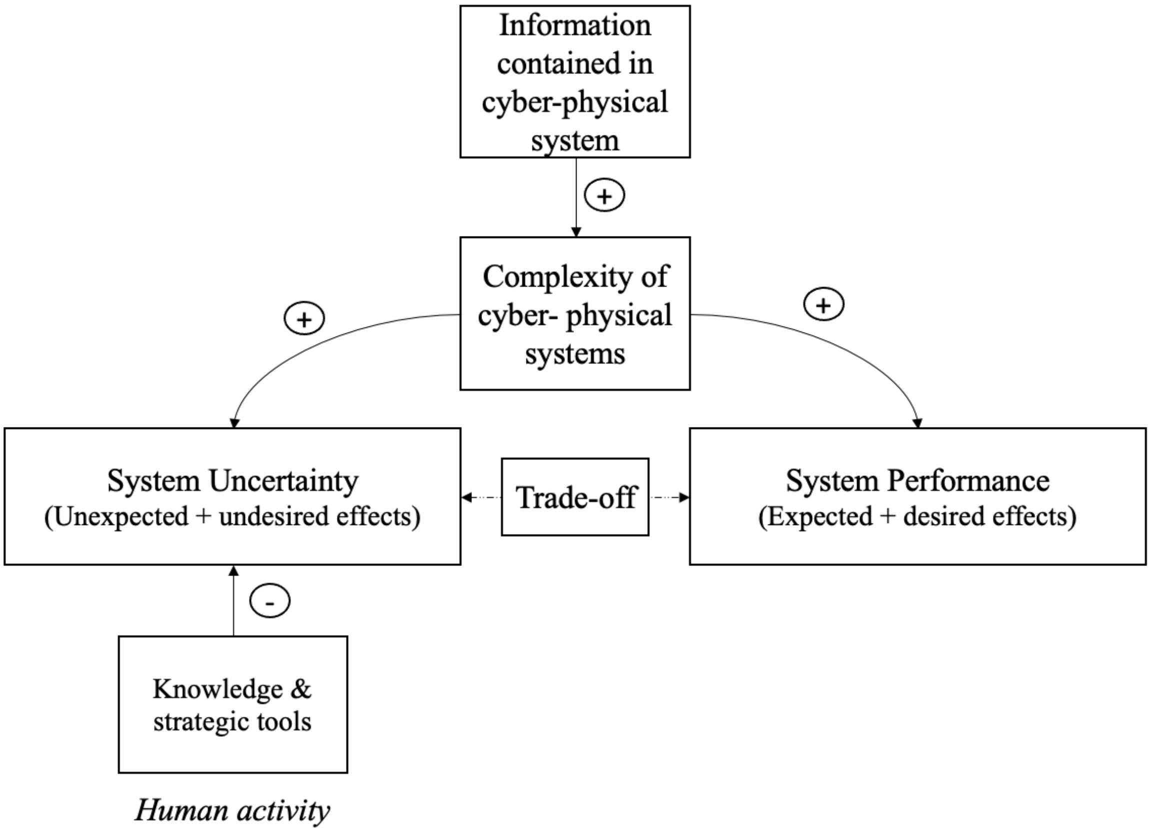



*Figure 69: Human activity in the context of the impact of complexity on CPS*

Figure 69 shows that it can now be established that human activity in the context of strategic complexity management in CPS is primarily aimed at system uncertainty reduction via the generation of knowledge and the practical application of strategic tools.

The next section now provides an overview of the established hypotheses for this thesis.

## 9.6 Overview of established hypotheses

This section now provides an overview of all hypotheses H1-H13 established.

### 9.6.1 Hypotheses concerning system behaviour & system environment of complex industrial systems

H1-H4 provide theories concerning the behaviour of complexity as information in industrial systems. These are now displayed in Table 14.

*Table 14: Overview H1-H4*

| Hypothesis | Description |
|---|---|
| **H1** | *The amount of information in a system is represented by the amount of data stored and recoverable by agents contained in the system* |
| **H2** | *Any type of information flow in a given industrial information system can be explained by a given combination of sources of information positioned in a network constellation in the form of agents.* |
| **H3** | *Any type of information flow in a given industrial information system in the form of CPS can be expected to generate cascadic growth of circulated information if an undistorted feedback loop is in place.* |
| **H4** | *The complexity of an industrial information system is defined by the amount of information contained and produced in the system with more information leading to more complexity and vice versa.* |

The next section now displays the hypotheses introduced for the dimension of decision-making.

### 9.6.2 Hypotheses concerning decision-making for complex industrial systems

H5-H13 provide theories concerning the impact of complexity on the decision-making process in industrial systems. These are now displayed in Table 15.

*Table 15: Overview H5-H13*

| Hypothesis | Description |
|---|---|
| **H5** | *If a system maximizes its set of system disturbances, the set of regulatory responses must also be maximized.* |

| | |
|---|---|
| **H6** | *If a system maximizes its set of system disturbances, the set of possible outcomes must also be maximized.* |
| **H7** | *The choice set of a rational decision-maker in the role of a system regulator is equal to the set of regulatory responses.* |
| **H8** | *If a system maximizes its set of disturbances, the resulting choice set of a regulating decision-maker is also maximized.* |
| **H9** | *If a system maximizes its set of disturbances, the necessary knowledge in form of information about the system a decision-maker must have to attribute objective probabilities is also maximized.* |
| **H10** | *If a system maximizes its set of disturbances, the resulting uncertainty in a choice set of a regulating decision-maker is also maximized.* |
| **H11** | *If a system maximizes its set of disturbances, the risk contained in a choice set of a decision-maker is also maximized.* |
| **H12** | *If a system maximizes its set of disturbances, the risk contained in a choice set of a decision-maker can be minimized through the application of heuristics models.* |
| **H13** | *If a system maximizes its set of disturbances, the risk contained in a choice set of a decision-maker can be maximized through the application of optimization models.* |

As a summary, Figure 70 now provides an approximation of H1-H13 in a final overview.

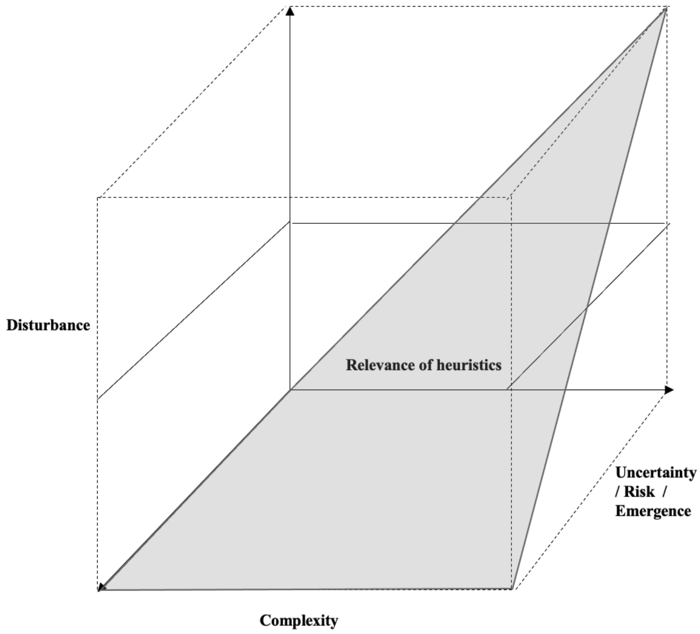



*Figure 70: Overview of the general implications of H1-H13*

Figure 70 illustrates that H1-H13 establish a direct relationship between the dimensions of complexity, disturbance, uncertainty / risk / emergence, and the relevancy of heuristics in this context.

Consequently, it is shown that the relevancy of heuristics is directly dependent on the other dimensions and significantly increases as the complexity of a system increases.

H1-H13 now allow to coherently answer SRQ1 and O1 of this thesis:

- ***Sub-research question 1 (SRQ1; O1):*** **How can the nature of complexity in industrial systems and its impact on decision-makers be defined?**

  ***Answer:*** Based on the achievement of O1 through H1-H13 it can be coherently argued that the importance of the application of heuristics for industrial complex systems management / decision-making is expected to increase in importance at least in proportion to any increase of complexity, disturbance and system uncertainty in the system behaviour and system environment.

After answering SRQ1 and achieving the corresponding objective O1, the next chapter now presents a coherent definition of industrial system complexity via a complexity space modelling approach to answer SRQ 2 and to achieve O2.

# 10 Modelling industrial system complexity

To answer SRQ2 and achieve O2 this chapter introduces an approach, based on H1-H13, to model the complexity of a system in a three-dimensional Euclidean space with the means of a set of theoretical axiomatic assumptions concerning the developed definitions of static and dynamic complexity. This chapter thus also has the goal to adhere to axiom A2: *characterizing complexity*.

The core motivation of this chapter is to answer to the key-challenge of developing conceptual complexity models which can deliver instrumental value via uncertainty-reducing, communicative or strategic purposes in the decision-making process between different stakeholders (for example system engineer and manager).

Such a model can also serve as a first baseline to be developed to more determinate and executable simulation models and frameworks in the future, for example through supporting the development of in-depth and specialized mathematical formalisms, coded computational methods like computer algorithms or as a theoretical baseline for SMTTs in order to solve problems in relation to complexity of industrial systems. (Fujimoto et al., 2017, Petnga & Austin, 2016)

To achieve this, the chapter introduces a novel conceptual "complexity space-based" approach as shown in the research of Freund et al. (2021c) and Freund & Al-Majeed (2020b) to model, quantify and visualize the complexity of modern and future industrial systems in a way that supports the visualization and potentially simulation of the complexity of both the physical and the informational system layers and their respective information flow in a three-dimensional complexity space model.

The proposed model is to be regarded as an early-stage artifact that integrates two different complexity dimensions, as well as provides axiomatic requirements for more specialized, formal, and mathematically operable models and which allows exploratory analysis of complex industrial systems.

Exploratory analysis is focused on describing ranges of possible system development trajectories and extreme behavior patterns or drastic changes in the system while focusing on endogenous and system internal complexity dynamics. (Fujimoto et al., 2017, Johnson et al., 2012)

To adhere to the concept of exploratory analysis, the aim of this chapter is to introduce a perspective on complexity modelling that represents industrial system complexity through conceptions of static and dynamic complexity dimensions via an integrated, compounded state in a conceptual model, the concept of complexity space.

The proposed complexity space model now has the following functions:

- Characterize the basic constituents and/or governing dynamics of industrial system complexity in a coherent framework via the introduction of complexity space in line with the propositions introduced by H1-H13.
- Provide a coherent understanding of the dimensions and factors that unify the complexity of industrial systems.
- Serve as an early-stage artifact component or starting point for more advanced modelling, simulation or SMTT approaches for complex industrial systems management.
- Enable early-stage exploratory analysis for industrial system analysis.
- Supporting the decision-making process between different system stakeholders through reducing uncertainty about the systems properties, for example in the strategic system management or design process of the system.

Based on this, the next chapter now introduces the applied conception of complexity for the proposed model.

## 10.1 Applied conception of complexity

As already shown, complexity has many metrics, dimensions and definitions and has been defined as the measure of uncertainty or difficulty in achieving the functional requirements of a system within the ranges of its design. (Petnga & Austin, 2016, Ragavan & Shanmugavel, 2016, Deshmuk et al., 1998)

The described two conceptions of complexity shall be applied for the proposed modelling approach:

- Static / structural complexity
- Dynamic complexity

Static or structural complexity shall now be defined as how the industrial system is structured (e.g., number of processors/machines, machine connections and interconnections). (Sheard & Mostashari, 2010)

Dynamic complexity is now defined as a measure of the unpredictability in the behavior of the system over a time-period based on information entropy. A common example of dynamic complexity is any type of unwanted system behavior, like a machine breakdown. Dynamic complexity is thus the core obstacle to achieving the systems target function. (Ragavan & Shanmugavel, 2016, Deshmuk et al., 1998, Frizelle, 1996)

Both types of complexity shall serve as the two foundational dimensions of the applied complexity modelling approach.

Both dimensions represent reliable measurement dimensions for complexity for modelling approaches, for example Defense Advanced Research Projects Agency (DARPA) of the US Government expects complexity of next generation products to reach 1.0E+08, measured in parts and lines of code. (Ragavan & Shanmugavel, 2016)

The notions of static and dynamic complexity make also visible that the presented model focuses on system intra-dependency, the internal complexity of the layout of the manufacturing system. For simplicity, the model does not regard stand-alone equipment complexity, stand-alone environmental system complexity or any external factors that may impact system complexity, if not stated otherwise.

In the next section the idea of the inherent spatiality of complexity as a the core foundation of the developed model is introduced.

## 10.2 The inherent spatiality of complexity

The proposed model shall now be based on the notion that complexity is inherently of a spatial nature.

Consequently, interactions among system elements are spatially structured in ways that contribute to the evolution of the spatial structure in which they play out. Complex manufacturing systems shall be regarded for this thesis as dynamic networks of various nodes and linkages between processor unites created in space operating in a particular place. (Koehler, 2014, O`Sullivan et al., 2006)

Space shall be defined in this context as a construction of where system behaviour is organized as relationships of system components via complex interactions. (Koehler, 2014)

Space shall therefore be defined as an “openness” in which the relations and the interdependencies that come with it matter for the explanation of individual system parts or the collective behaviour of the system. (Koehler, 2014)

Space shall therefore be assumed to function as a static theoretical compound state, a “container”, of related, abstracted, and subjective dimensions of perception in which system behaviour is organized and complex, time-dependent emergent dynamic system behaviour can occur.

In the case of information systems, the concept of spatiality is already introduced by Hepworth (1987), especially in the area of early computer networks and already underlines the notion that system spatiality is often overlooked due to its cyber-physical nature and that information environments are often taken for granted by users. This phenomenon is compared by Hepworth (1987) to the well-known allegory of the fish that is not aware of the water in which it swims.

Building on these propositions, complexity science for complex industrial manufacturing systems shall be concerned with simultaneous spatial and temporal analysis of industrial systems. (Klamut et al., 2020)

In the proposed space-based complexity model the spatial analysis shall be centred around the concept of static industrial system complexity while the temporal analysis shall be defined by the concept of dynamic complexity.

Figure 71 illustrates the chosen approach for the model established in this thesis.

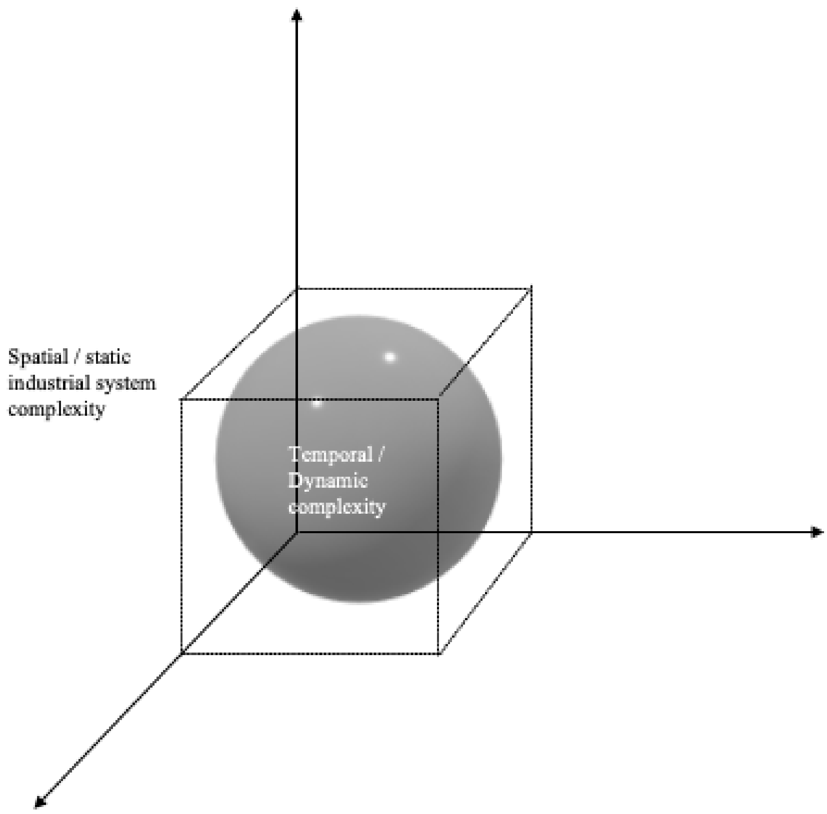



*Figure 71: Basic components of complexity space modelling approach*

Figure 71 shows that in the proposed model the spatial dimension is defined as the static complexity of the represented system in a 3D space. The resulting extent of the "complexity space" of the static compound state is now functioning as the container for the temporal component of the model which represents the dynamic complexity of the system at a given point time.

Based on these thoughts the next section now briefly discusses the general concept of space-based modelling for complex manufacturing systems before defining the concrete modelling approach for this thesis.

### 10.2.1 Related complexity concepts to complexity space

To underline the applicability of the chosen model, this section now briefly touches upon the utilization of "space-based" models in the complexity literature.

Next to the already introduced concepts of Schelling´s model or Ashby space, the concept of complexity space can be seen in the tradition of possibility space as developed by McCarthy & Tan (2000) who utilized a three-dimensional cube is used to represent the possible space of solutions and how they relate to each other to investigate the process of self-organization and natural selection in the fitness landscape of a given manufacturing system.

Hatna & Benenson (2012) introduced a similar concept in their studies of the Schelling model in the form of a parameter space.

Mourtzis et al. (2019) introduce an information-based entropy space for industrial systems.

The next section now further expands on the dimensions of the proposed complexity space model before introducing the model itself.

## 10.3 Static industrial system complexity

The concept of static industrial system complexity ($S_C$) shall be defined by the static, time-independent architectural layout of a manufacturing process represented by machines /operations (m), their connections via links (l), and their interconnectedness via gates (g) as shown by equation (16).

$$(16) \qquad SC = \{m, l, g\}$$

This definition offers a more nuanced definition than just the often-used simple enumeration of the number of system parts as a starting point for system complexity modelling. It must be mentioned at this point that the number of parts, connection and gates do represent a multi-dimensional quantity, as for example a machine may contain several subsystems. It is thus necessary to apply pre-defined levels of abstraction to allow system representation in the form of pre-set system boundaries and pre-defined system entities. (Mourtzis, 2019, Frizelle, 1998, Gharbie, 2012, Wortmann, 1991)

The next section now further elaborates on the assumptions made for the proposed model.

### 10.3.1 Modelling assumptions

These pre-set and pre-defined boundaries and entities shall be utilized as abstractions, to allow a formalized modelling of industrial manufacturing systems to narrow down on the issue on system complexity via a clearly defined set of parameters.

For the case of the model, an industrial system shall be defined as a manufacturing system.

Any manufacturing system itself shall be regarded as a flux of material (input) going through a transformation process (adding information), consisting out of machines, links and gates, which then results in a flux of output materials (products) with a higher complexity. (Mourtzis, 2019, Frizelle, 1998, Gharbie, 2012, Wortmann, 1991)

This is illustrated by Figure 72.

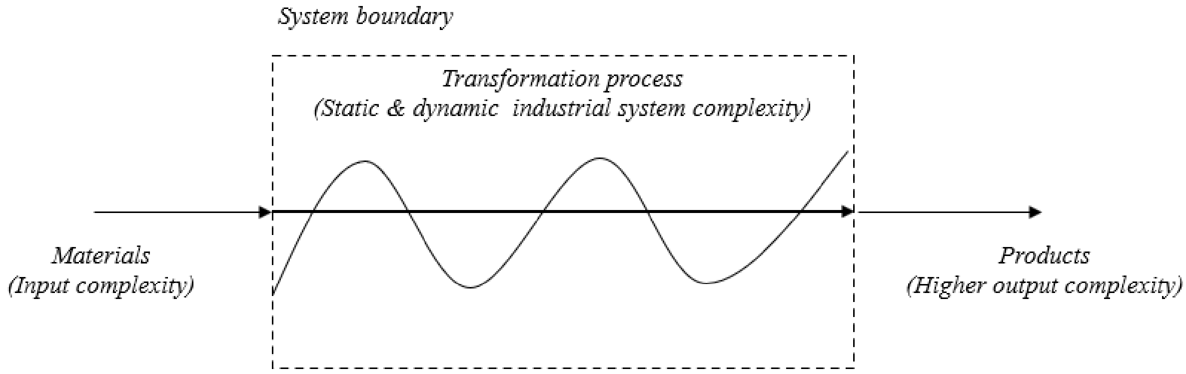



*Figure 72: Manufacturing system*

In the context of industrial system complexity, the term machine (m) shall be defined as an agent, a physical processor / receptor / effector of information in the transformation process of a manufacturing system, an active element or artifact, that performs actions in the form of processing information via transformation of energy, material, and information. An action is defined as a change in the state of the model, e.g., any action contained in the transformation process.

Different processors can execute in parallel, and they proceed with the performance of actions independently or dependent of each other. This means that different processors can be active at the same time or can function in a sequential manner.

A machine shall also be capable to function as an expanded processor. This means that a machine encompasses a given set of sub-processors in the form of operations. For example, a manufacturing machine could contain two sub-operations in the form of a packaging machine and a manual operator. (Mourtzis, 2019, Gharbie, 2012)

The term links (l) shall refer to interaction pathways between machines in the transformation process where information is passed from one machine to the other, for example in the form of materials over conveyor belts, intermediate products, or wireless data flows in the already described receptor / effector / processor logic.

It is thus modelled that material or immaterial objects can flow from one processor to a receptor / processor / effector only if processors are connected via links, allowing them to be effectors.

The term gate (g) shall refer to connection points where links connect machines within the system.

Gates specify interaction and decision-points between processors and thus define the modus operandi of how different processors interact with each other in a system, for example through digital interfaces, machine interfaces, manual quality tests, sensors, or others. (Gharbie, 2012, Wortmann, 1991, Sheard & Mostashari, 2010)

Consequently, a gate transforms the information that is send by one processor to another via links, so that the receiving processor unit can process and transform the received information in a correct fashion, effectively providing the receptor of information the capability to function as a processor.

This assumption is based on the research Toro et al. (2003) who state that the number of components in an assembly system can be regarded as a precise indicator for system complexity.

The next section now further elaborates on the dimensions of static industrial system complexity.

### 10.3.2 Dimensions of static industrial system complexity

The conception of static complexity leads to the conclusion that the static and time-independent complexity ($S_C$) of an industrial production system shall be reduced to, captured, and quantified by three dimensions:

- **Structural complexity (Cs):** Machine layout
- **Connectivity complexity (Cc):** Link layout
- **Interconnectivity complexity (Ci):** Gate layout

Figure 73 illustrates the three dimensions by showcasing the block chart of a hypothetical production system (S1) based on the complexity dimensions machines, links and gates.

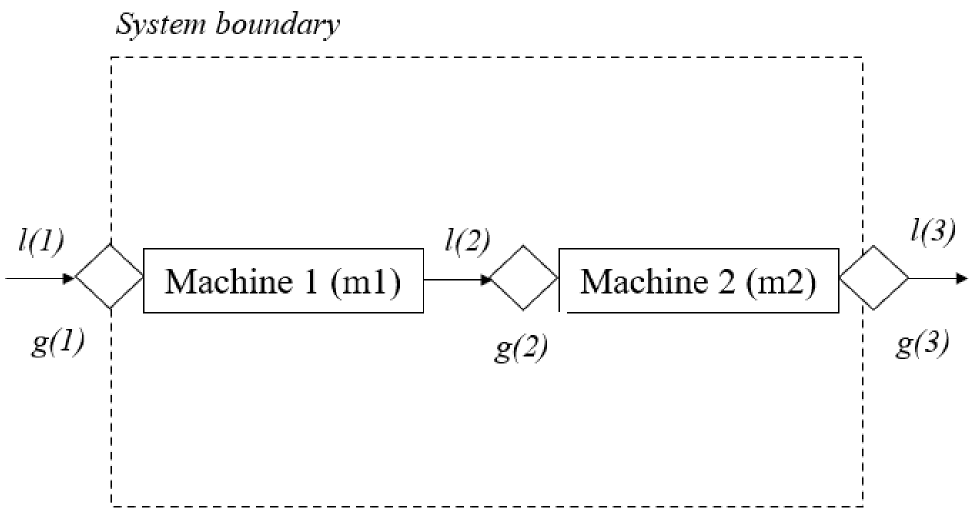



*Figure 73: Abstraction of manufacturing system*

Figure 78 shows, that S1 consists out of a machine layout with two machines, with m(1) and m(2), which are connected by a link layout with three links, with l(1)-l(3), and which interconnect with a gate layout of three gates, with g(1)-g(3).

Based on this, the next section now introduces the concept of complexity space.

## 10.4 Complexity space

The modelling of the static complexity of a manufacturing system shall now be expressed by the theoretical three-dimensional compound state volume that results from the three dimensions combined, which shall be named complexity space of a system with the volume ($V_{Cspace}$).

This is now illustrated in equation (17).

$$VCspace = Cs \; x \; Cc \; x \; Ci \qquad (17)$$

*Where* Cs is the machine layout (structural complexity), Cc the link layout (connectivity complexity) and the Ci (interconnectivity complexity) the gate layout of a given system.

This is illustrated in Figure 74 accordingly.

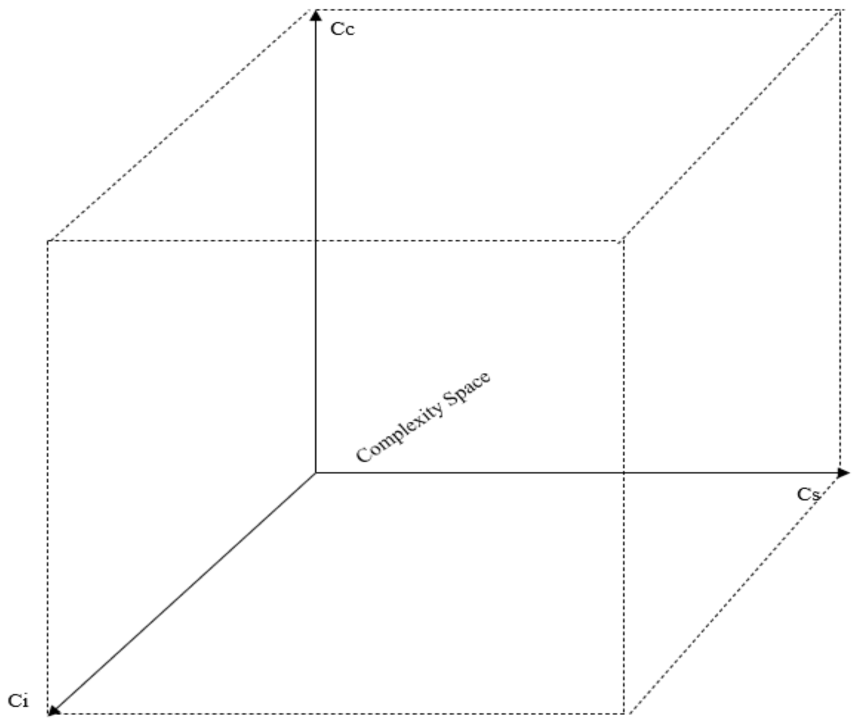



*Figure 74: Complexity space*

The theory of complexity space can now be applied as a foundational basis for system complexity Modelling and visualization of static industrial system complexity ($S_C$) of a manufacturing system.

Equation (18) reflects this.

$$(18) \qquad VCspace = SC$$

Equation (18) shows, that ($V_{Cspace}$) can now be utilized to represent the compound state of ($S_C$) for this study.

The three dimensions (Cs, Cc, Ci) of complexity space ($V_{Cspace}$) are assumed to comprise the variables of the compound state of the complexity of the static structure of a modeled manufacturing system.

The basic arrangements and relations between the individual system parts in the form of machines, gates and links and are now further described.

The logarithm to the base of 2 is utilized to decrease the impact of higher numbers in the different dimensions and to allow a quantification in units of bits. (Gharbie, 2012, Johansson, 2002)

### 10.4.1 Structural complexity

(Cs) shall be defined by a systems structural, static layout of machineries (m). Consequently, (Cs) of an industrial production system is expected to be maximized if (m) is maximized.

This is shown in equation (19).

$$(19) \qquad Log2(m) = Csmax$$

*Where* m=number of machines and Cs=structural complexity of the system.

### 10.4.2 Connectivity complexity

(Cc) shall be defined by a systems structural, static layout containing transfer links (l) between the system machinery layouts. Consequently, (Cc) of an industrial production system is expected to be maximized if (l) is maximized.

This is shown in equation (20).

$$(20) \qquad Log2(l) = Ccmax$$

*Where* l=number of links and Cc=connectivity complexity of the system.

### 10.4.3 Interconnectivity complexity

(Ci) shall be defined by a systems structural, static layout of number of gates (g) connecting different transfer links to the system static structural machinery layout and types of gates, for example data or material gates.

Consequently, (Ci) of a manufacturing system is expected to be maximized if (g) is maximized.

This is shown in equation (21).

$$(21) \qquad Log2(g) = Cimax$$

*Where* g=number of gates and Ci=interconnectivity complexity of the system.

The definition of the complexity dimensions shows that the total volume of the complexity space ($V_{Cspace}$) of an industrial system can be maximized by maximizing each complexity dimension and is calculated in units of bits via the use of a base-2 logarithm to encode all static system states in information and to reduce the overall impact of larger dimension sizes on the overall complexity space volume.

($V_{Cspace}$) can now be calculated a space of information in units of bits as shown in equation (22).

$$(22) \qquad VCspace = Log2(m)\ x\ Log2(l)\ x\ Log2(g)$$

*Where* $V_{Cspace}$ = complexity space volume of the system and $Log_2(m)$ = Cs, $Log_2(l)$=Cc and $Log_2(g)$=Ci.

After introducing the concept of complexity space and complexity space volume as the metric for static system complexity in detail, the next section now describes briefly expands on the integration of multiple system levels in complexity space.

## 10.4.4 Multiple system levels in complexity space

Figure 75 now illustrates a multi-system-layer complexity space model by introducing a hypothetical layer of complexity spaces of a hypothetical automotive factory system (S1 contains S2, S2 contains S3) positioned in complexity space.

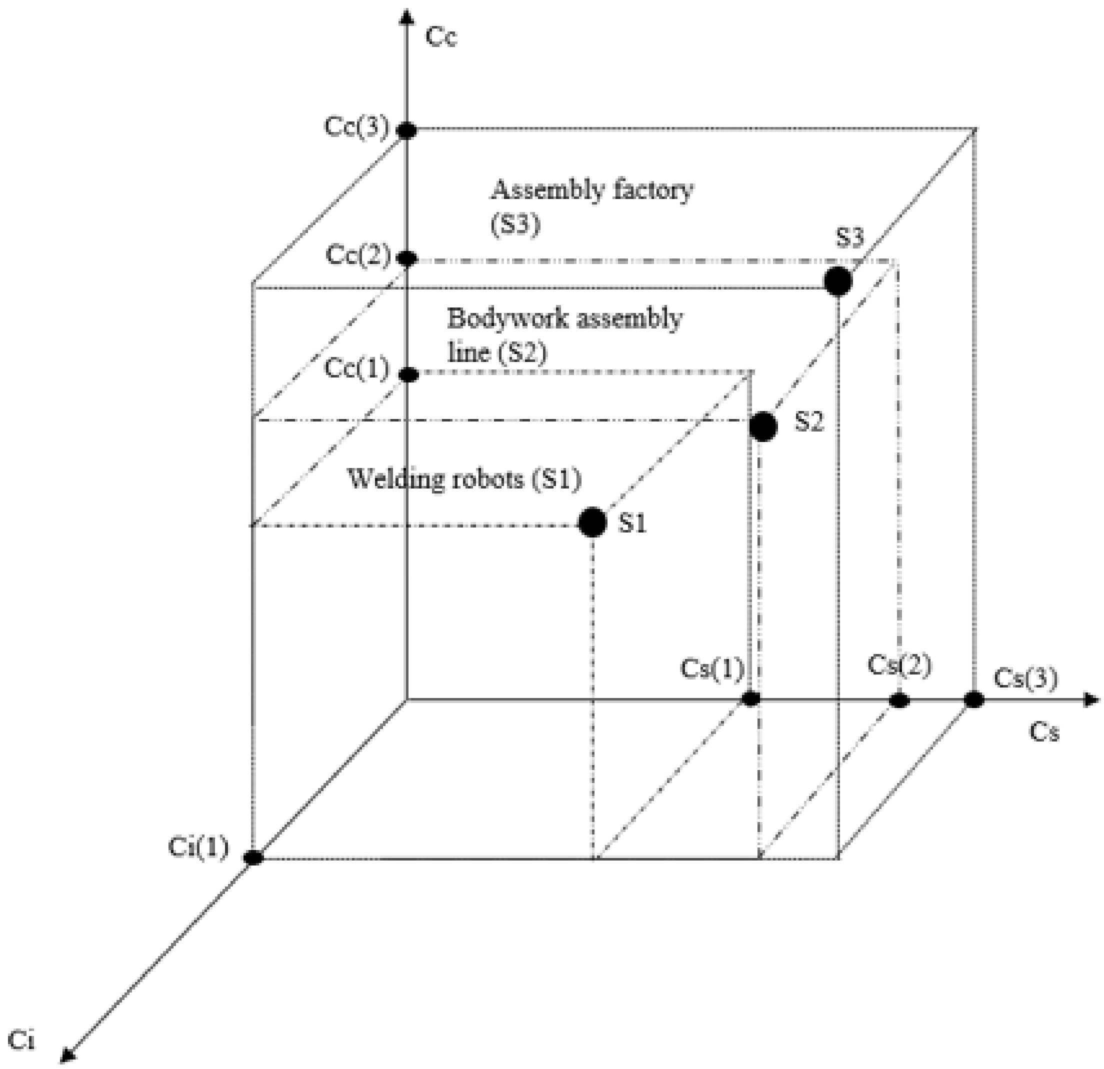



*Figure 75: Levels of a system in complexity space*

Based on the provided example it can be shown that multiple system levels of a manufacturing system can be captured and visualized in complexity space model at once, allowing the representation of different system layers in the model through the utilization of complexity space.

Based on this notion it is now possible to introduce and integrate a dynamic complexity component to the model in the form of a definition of dynamic complexity.

## 10.5 Dynamic complexity in complexity space

As defined in H1-H4, a common dominator of dynamic complexity shall be introduced through the notion of system information entropy. As stated, the entropy of a system is in this context regarded as a measure of disorder in the system and fits the applied conception of Deshmuk et al. (1998) and Klamut et.al (2020).

Based on this notion, a dynamic element of industrial system complexity in the form of information complexity is conceptualized and serves as an information entropic indicator for system instability and decision-risk when integrated in the complexity space model of a manufacturing system, as defined in H1-H13.

### 10.5.1 Properties of dynamic complexity

Dynamic system complexity shall be associated with three main properties:

- **Qi:** Quantity of information
- **Vi:** Variety of information
- **Hi:** Information content

These properties correspond dynamically and time-dependent to the transformation efforts in a manufacturing system to achieve the high output complexity in correspondence to a given production goal within a given industrial system. (Frizelle, 1998, Mourtzis, 2019, Gharbie, 2012)

Consequently, the dynamic system complexity in the form of information complexity ($C_N$) is proposed to represent the quantity, variety and information content of information contained in a system at a given point in time.

Equation (23) illustrates this.

$$(23) \qquad CN = \{Qi, Vi, Hi\}$$

*Where* $C_N$ = Information complexity, Oi= information quantity, Vi= information variety and Hi= information content.

Based on this the next section now introduces the concept of information complexity as machine memory space.

## 10.5.2 Information complexity as machine memory space

To allow a potential practical application of the model, a given machine (m) in a manufacturing system shall be expected to utilize a given amount of information (N) to contribute to the transformation process of the system. To allow a more nuanced and practical definition of the term information it is possible to introduce the concept of machine memory space (mms). (Johansson, 2002, Cilliers, 2002, Yanofsky, 2006)

A machine (m) in a manufacturing system and the system itself shall for this purpose be regarded as algorithms, a sequence of well-ordered instructions (input), that serve to solve a well-formulated problem (output) to obtain the overall goal of the system. (Yanofsky, 2006)

($mms_{system}$) now describes the total amount of memory space units and therefore the extent of the encoded information content (Hi), quantity (Qi) and variety (Vi) needed by the static layout of a system to produce the expected solution as an output in relation to its input instructions.

Equation (24) illustrates this.

$$(24) \qquad mmssystem \ = \{Qi, Vi, Hi\}$$

*Where* $mms_{system}$= amount of system memory space, Oi= information quantity, Vi= information variety and Hi= information content.

For example, in the case of a linear programming problem this process shall be defined as the problem of either minimizing or maximizing a linear function subject to a finite set of linear constraints, for example with a simplex algorithm. (Yanofsky, 2006, Heintz et al. , 2001, Comen, 2009)

The total information complexity contained in a system ($C_N(T)$) can now be defined.

This is shown in equation (25).

$$(25) \qquad Log2(mmssystem) = \ CN(T)$$

*Where* $mms_{system}$= amount of system memory space and $C_N(T)$= total information complexity contained in a system.

It can now be stated that a system must be regarded as non-complex if no or only minimal information is flowing, irrespective of the size of complexity space volume.

## 10.6 Information complexity within complexity space

The introduced definition of information complexity in H1-H4 can now be integrated in the concept of three-dimensional complexity space and shall be assumed to take the form of an information complexity sphere with a volume ($V_{Sphere}$) situated in ($V_{Cspace}$), with ($V_{Cspace}$)>($V_{Sphere}$), (($V_{Sphere}$), ($V_{Cspace}$))>0.

To achieve this a hypothetical information complexity inception point (I(S)) is assumed to exist at the center of complexity space. From I(S) the total information complexity ($C_N$(T)) is expected to expand in all directions into complexity space over time as the static layout of the system circulates, stores and generates information via machines, gates and links.

For simplification, the volume of the information complexity shall be defined by the conception of information complexity as a spherical body that occupies complexity space, where ($C_N$(T)) is regarded as the radius (r) of the information complexity sphere situated in the complexity space. This is shown in equations (26) and (27).

$$(26) \qquad VSphere = \frac{4}{3} x \, \pi \, x \, CN(T)3$$

$$(27) \qquad VSphere = \frac{4}{3} \, x \, \pi \, x \, Log2(mmssystem\,)3$$

Equations (26) and (27) are now integrated into complexity space as displayed in Figure 76.

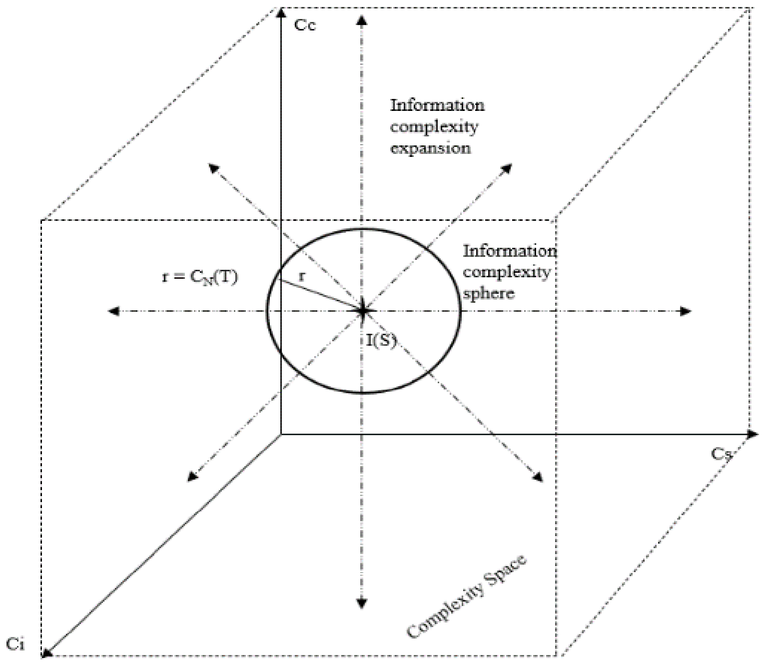



*Figure 76: Information complexity in complexity space*

Based on H1-H4 and Figure 76 it shall furthermore be assumed that the informational complexity of an industrial system increases over a timespan t0-tn when the input / output instructions of the system change over time and no mitigating or inhibiting regulations of the system are in place.

Figure 77 illustrates this.

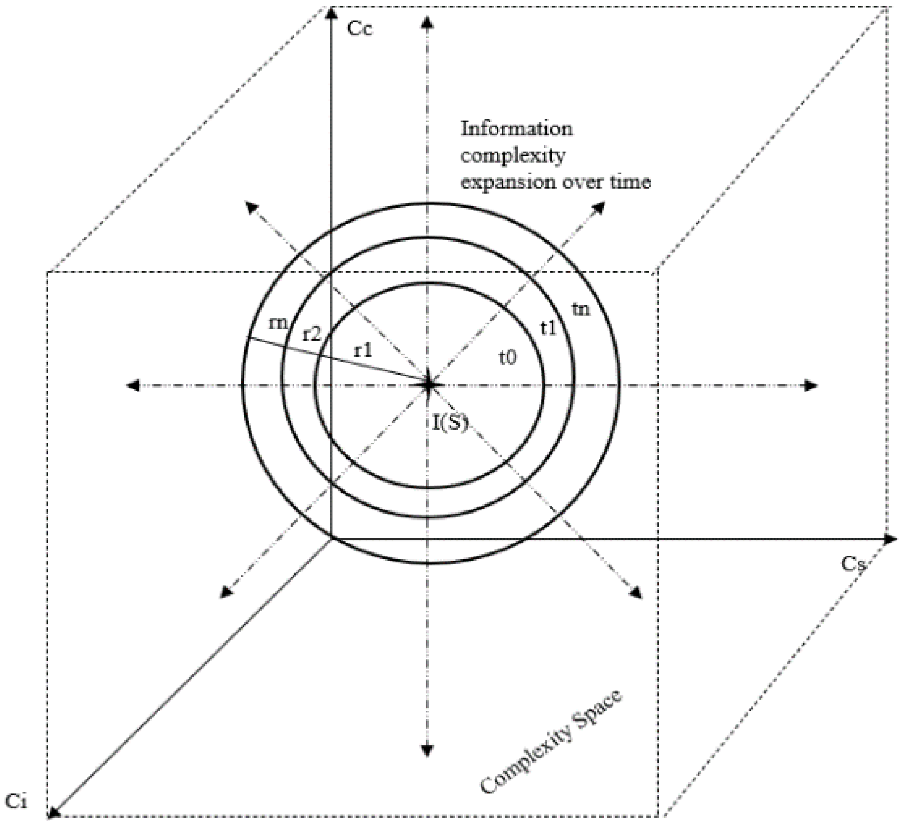



*Figure 77: Expansion of information complexity in complexity space*

Consequently, a manufacturing system that is expected to function under varying input / output instructions as an algorithm to meet changing system transformations can be expected to maximize the volume of its information complexity sphere over time.

This is shown by Lehman´s Law of increasing complexity, which states that a systems complexity must increase over time if the system is not artificially regulated and by the laws of entropy in a system, exemplified in the second law of thermodynamics. (Ragavan & Shanmugavel, 2016, Johansson, 2002, Godfrey & German, 2012, Lent, 2018)

Information complexity thus suggests the expenditure until the boundary of the systems complexity space is reached over time.

The application of Ashby´s law of requisite variety and H5-H13 allow to draw definitive conclusions concerning an increase of regulation effort or hidden cost of the system over time in proportion to informational complexity as modeled in complexity space. (Ashby, 1991)

### 10.6.1 System distortion

The volume of the complexity space of a manufacturing system resulting from the dimensions (Cs), (Ci) and (Cc) predefines the theoretical limits for the expansion of ($C_N$) and the maximum volume of the information complexity sphere.

If expansion of ($C_N$) is not inhibited, the radius of the information complexity sphere (rn) must reach the boundaries of one or more dimensions of the complexity space in a time (tn) and creates the distortion point D(S) in the given dimension(s).

When D(S) is reached the system shall be in a distorted state, leading up maximum deviation of the system target function in the distorted dimension and information complexity is unable to expand further in this dimension. This is in line with the assumptions described by Klamut et.al (2020) who state that the fully ordered system essentially has no complexity because of maximal possible ordered symmetry of the system, but the fully disordered system also contains no information, thus must be non-complex, as it distorts and eventually dissipates. It is thus concluded that maximum dynamic complexity must be positioned between these two extreme positions.

In this light, distortion in a system shall thus be defined as the upper limit of useful system operational ability where the system behaviour becomes random, chaotic and may dissipate.

Figure 78 illustrates this.

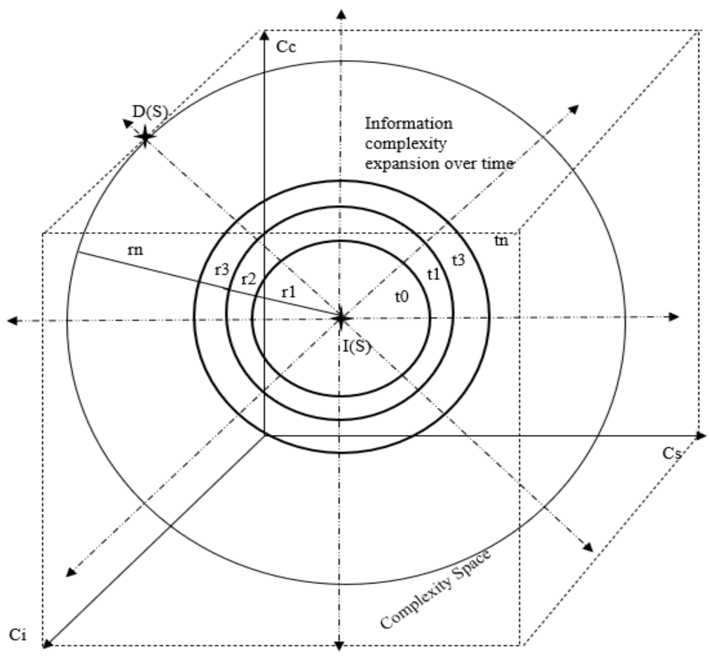



*Figure 78: System distortion in complexity space*

Based on Klamut et al. (2020), the expansion of information complexity in complexity space shall now be conceptualized via a logistic growth function.

This is shown in Equation (28).

$$(28) \qquad CN(T)(t) \ = \ CN0 \ x \ exp(kt) \ / \ (1 + d/k \ x \ CN0 \ (exp(kt) - 1))$$

*Where* $C_N(T)(t)$ = amount of information complexity at a given point in time t, $C_{N0}$ = amount of information complexity at t0, k=growth factor, d= degression factor.

Consequently, a convergence of the volume of the information complexity sphere (entropy) to its extensive asymptotic limit defined by the maximum complexity space volume of the system is to be regarded as a signature of dynamic complexity in complexity space and complexity in general.

Figure 79 now illustrates the assumptions made.

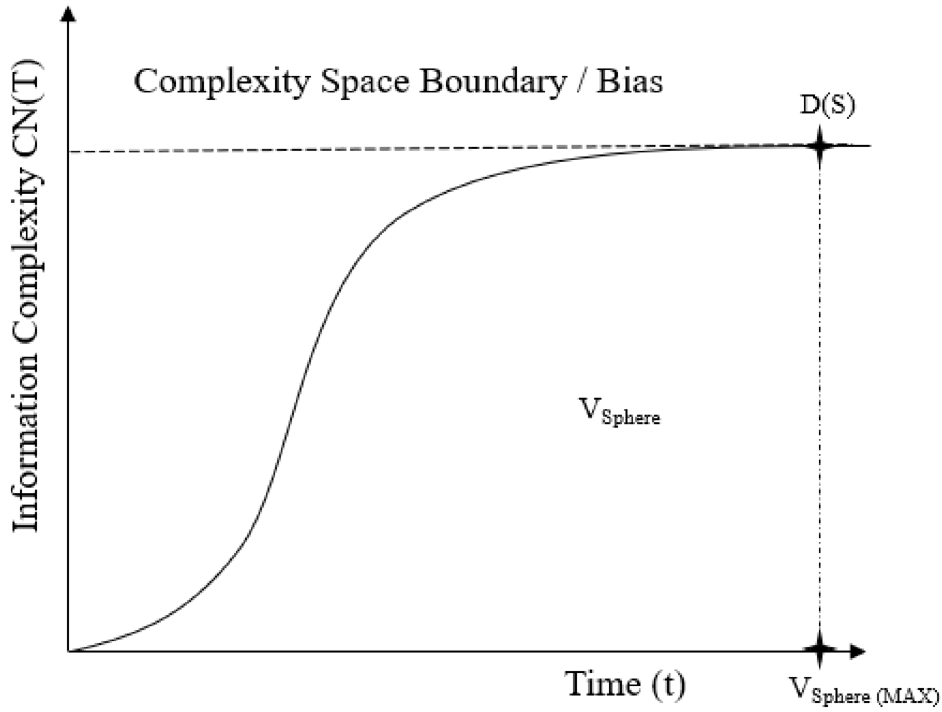



*Figure 79: Logistic growth function of information complexity expansion in complexity space*

Based on Equation (28), Figure 84 shows that $C_N(T)$ is now expected to show logistic growth behaviour over time (t0-tn) in the boundaries of complexity space.

While doing this, $C_N(T)$ is not only limited by the inherent degression factor of the function (d), representing any potential natural or superimposed inhibitor of information growth, but also by the volume of complexity space dimensions of the system in which the information complexity sphere expands until D(S), with $V_{Sphere\ (MAX)}$, is reached.

To illustrate the points made, the next section now covers multiple system layers with integrated information complexity spheres.

### 10.6.2 Multiple system layers with integrated information complexity spheres in complexity space

Figure 80 now illustrates how multiple systems with integrated information complexity spheres could behave to complete the picture by providing a complete first concept of environmental complexity in complexity space in which three systems (S1-S3) overlap in terms of complexity space and information complexity.

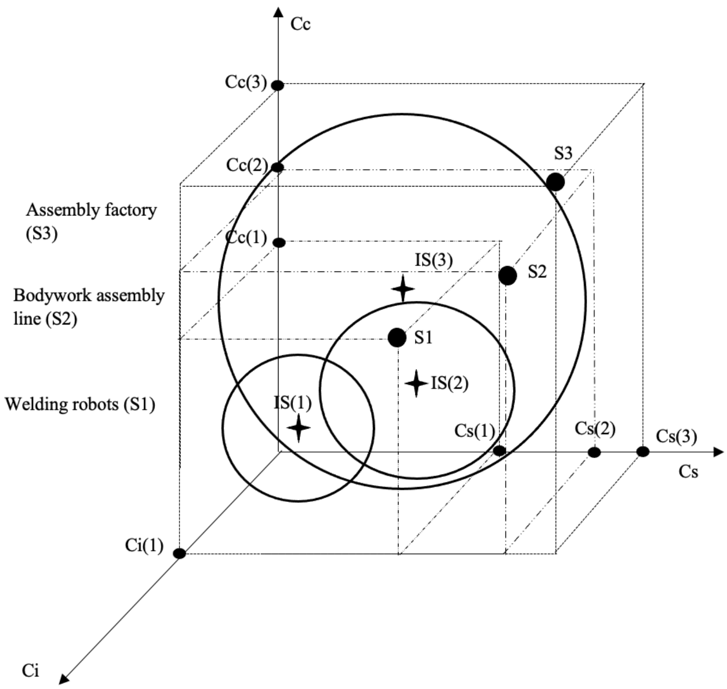



*Figure 80: Multiple system layers with integrated information complexity in complexity space*

In conclusion, the provided complexity space modelling approach now allows to draw the following implications for the scientific instrumental value of the approach:

- The model allows to characterize the basic constituents and/or governing dynamics of industrial system complexity in a coherent framework based on H1-H11.
- A coherent understanding of the dimensions and factors that unify the complexity of the analyzed complex system is achieved.
- The results can serve as a baseline component for more advanced modelling and simulation approaches for complex engineered systems

- The model can support the reduction of uncertainty in the decision-making process between different system stakeholders.

The mentioned implications show that the proposed complexity space modelling approach achieves its primary goals of enabling early-stage exploratory system analysis while serving as a potential conceptual baseline for more advanced system models and frameworks to solve problems of complexity in an engineering context.

A complexity space modelling approach for industrial system complexity based on H1-H11 is introduced and aims to serve as a conceptual modelling approach with the primary function of early-stage exploratory system analysis and enabling more advanced modelling and simulation approaches. The model is based on the axiomatic conception of a three-dimensional static complexity space in which informational complexity is modelled as a sphere that expands dynamically over time until expansion is limited by the boundaries of complexity space.

The complexity space model can furthermore be differentiated from more traditional space / phase models, as those models describe the trajectory predefined by equations of motion of a given system through a phase space by assigning a velocity vector in a vector field. (Mitra, 2018)

It can now be concluded in the context of the model, that any industrial system maximizes information complexity over time and thus also maximizes entropy over time, making the system increasingly prone to error, hazardous and cost intensive over time, if the system information complexity expansion is not adequately artificially controlled via an external control system of proportionate size and ability.

This now allows to answer SRQ2.

- ***Sub-research question 2 (SRQ2; O2):*** **How can industrial system complexity be theoretically modelled?**

  ***Answer:*** Industrial system complexity shall be modelled via a three-dimensional static complexity space in which informational complexity is modelled as a sphere that expands dynamically over time until expansion is limited by the boundaries of complexity space.

After answering SRQ2 and achieving the corresponding objective O2, the next chapter now presents the development of a strategic complexity management framework in order to answer SRQ 3 and to achieve O3.

# 11 Development of a strategic complexity management framework (SCM)

After achieving the SRQ1 & 2 and O1 & 2 of the thesis the theoretical foundation for the development of a strategic complexity management (SCM) framework is now established as the next step to fulfil A3 and SRQ3 / O4 of this thesis. This chapter thus also has the goal to adhere to axiom A3: *managing complexity*.

As shown in the work of Freund et al. (2021d, 2021e, 2021f), the resulting SCM framework is now introduced and is building upon the notions of the IKTF in Chapter 3, H1-H13 in Chapter 9, and the propositions of the developed complexity space model in Chapter 10.

The SCM is also inspired by the structure and function of proven, valued and practice based SMTTs like the described SWOT or BCG matrix.

Figure 81 now illustrates the SCM framework.

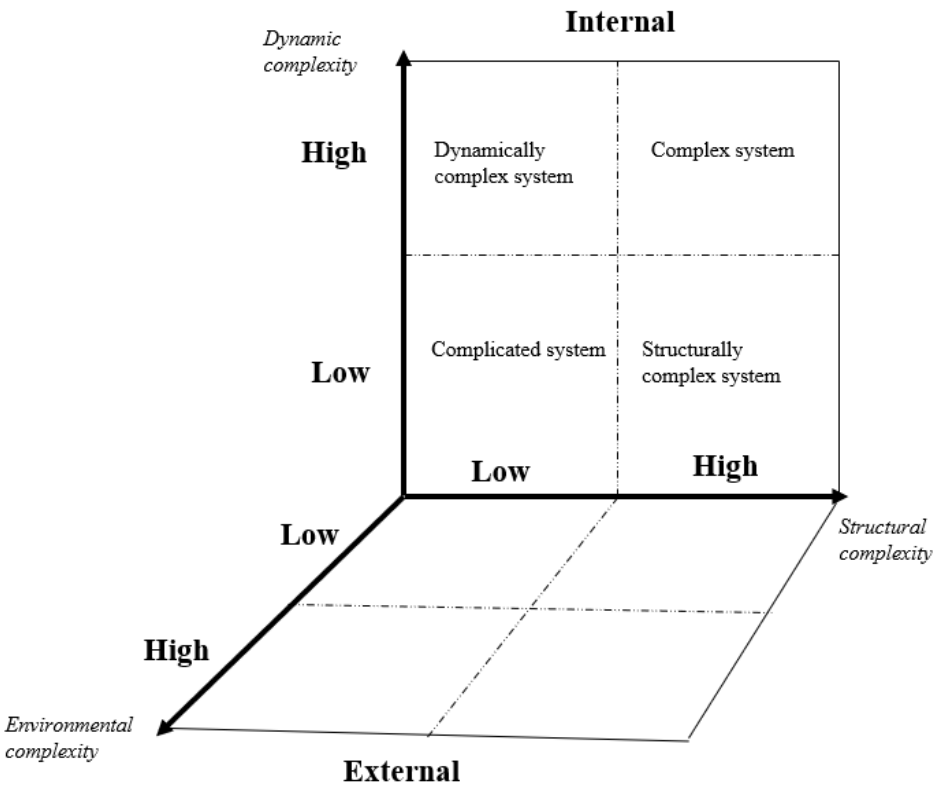



*Figure 81: Basic structure SCM framework*

Figure 81 shows, that the SCM is a SMTT that consists out of two generic 2x2 matrixes, resulting in an 8-quadrant matrix, with two perspectives of analysis (internal, external) in three complexity dimensions where structural and dynamic complexity represent the internal perspective and environmental complexity represents the external perspective of strategic management.

In this analysis The SCM now allows to qualify each complexity dimensions in a scale between HIGH and LOW.

The resulting intersections of the qualifications result in a system internal and system external classification leading up to a total system qualification and classification.

The next section now elaborates on the utilized SCM matrix approach.

## 11.1 Matrix-based approach for SCM analysis

Matrix-based approaches like the SCM have a long history in system modelling and analysis. (Kasser, 2018) Based on Lindemann et al. (2009) four different types of general matrix systems can be identified and applied for system analysis.

As shown in Lindemann et al. (2009) these matrix types are now illustrated in Figure 82.

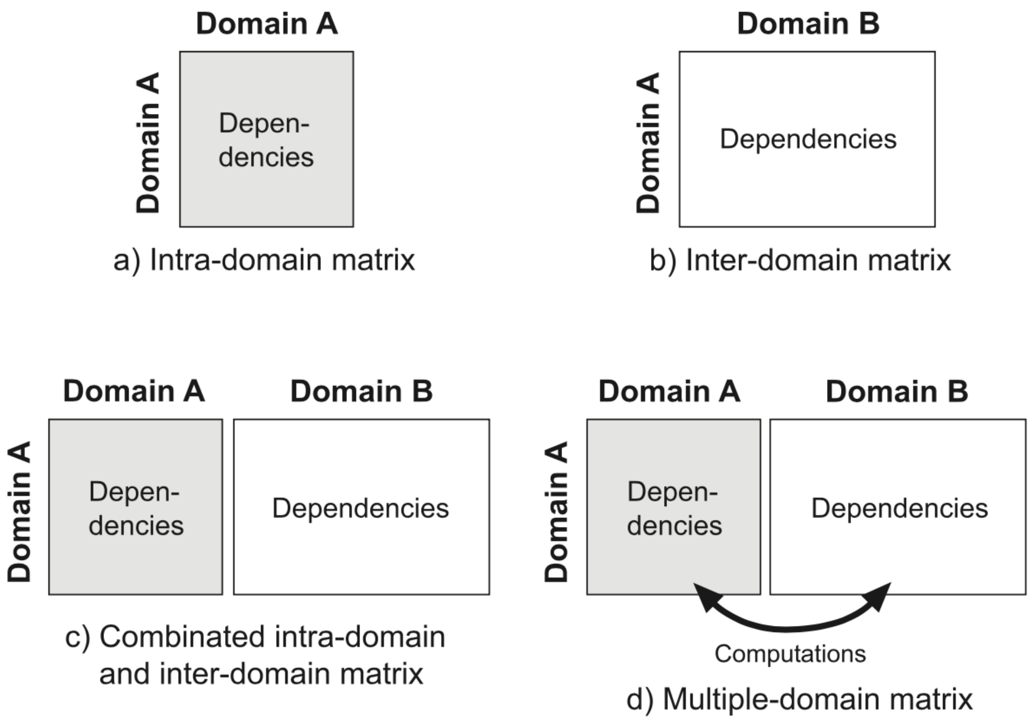



*Figure 82: Matrix domain types (Lindemann, 2009)*

Figure 82 makes visible that the SCM is best reflected by the concept of a multiple-domain matrix in which an intra-domain matrix, a square matrix that maps elements and their relationships in one domain via dependencies, for example the internal system complexity perspective, and a second domain and its interdependencies, for example the external system complexity perspective, are put together to a combined intra-domain and inter-domain matrix that allows systematic statements about the system.

The creation of the multiple-domain matrix includes the identification of required domains, the determination of system elements and their level of detail, and the linking of dependency types, meaning the mapping logics between specific domains.

Generally, the objective of creating the multiple-domain matrix is to identify required information sources and set up the basis for the systematic generation of knowledge about the system represented by the multiple-domain matrix. (Lindemann et al., 2009)

## 11.2 SCM complexity dimensions

As shown, the multiple-domain matrix of the SCM shall be based on three complexity dimensions, which are formulated for the application on current and future industrial systems:

- Structural complexity
- Dynamic complexity
- Environmental complexity

The proposed complexity dimensions suggest that there is a direct connection between the environmental complexity and its resulting uncertainty and the internal complexity of a system in the form of structural and dynamic complexity.

Figure 83 illustrates the interdependent relationship between all three dimensions.

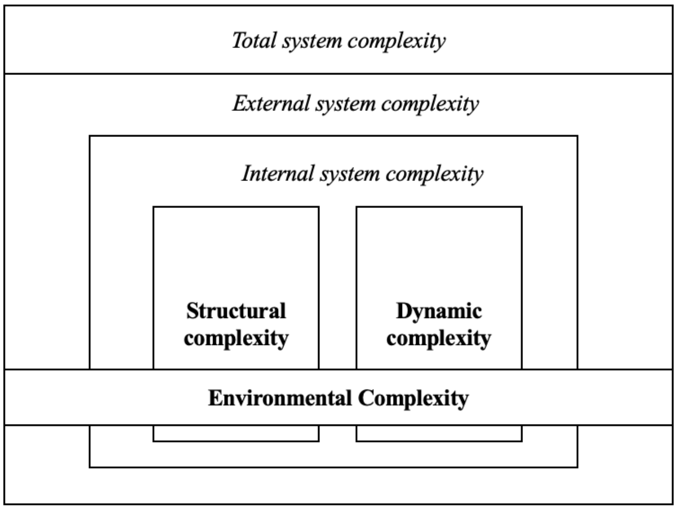



*Figure 83: SCM conception of system complexity*

Figure 84 builds on the established definitions and hypotheses and indicates that the greater the complexity of the system, the greater the amount of information that must be processed between decision-makers during its execution in every complexity dimension. (Junior et al., 2012)

This shows that any heuristic strategic analysis of the applied final complexity conception can only be valuable to the decision-maker if the analysis holistically integrates all mentioned dimensions of complexity in a balanced, coherent and strategic way.

This allows the decision-maker to assess the system and its behaviour as a whole and to identify as well as investigate individual drivers that influence system performance in the individual complexity dimensions. (Brinzer et al., 2017)

## 11.3 SCM core structure

The SCM is now based on three different complexity dimensions:

- Structural complexity
- Dynamic complexity
- Environmental complexity

Figure 84 illustrates the applied conception of complexity for the SCM in the form of three connected complexity dimensions as the core structure for the framework.

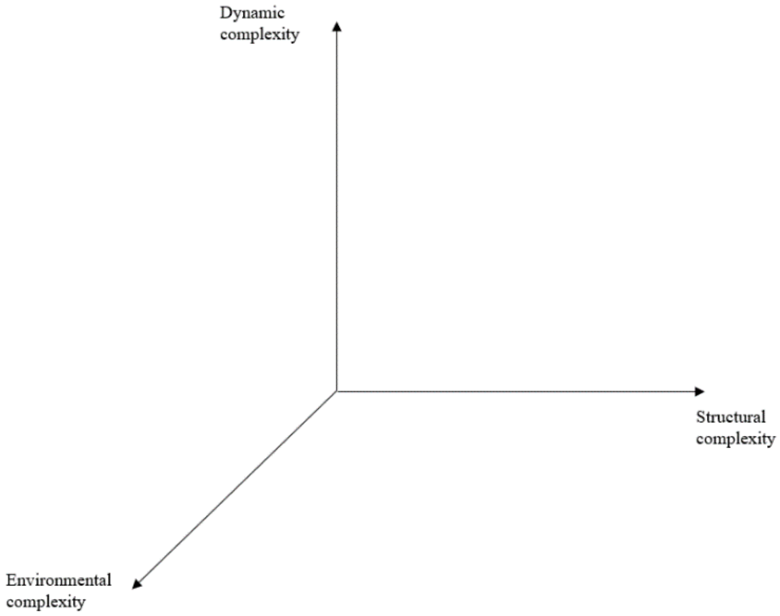



*Figure 84: SCM dimensions of complexity*

The next section now further expands on the chosen structure of the SCM in the context of the developed complexity space model.

## 11.3.1 The SCM structure in the context of complexity space modelling

Figure 85 now illustrates how the assumptions of the described complexity space model translate coherently into the development of the SCM basic structure.

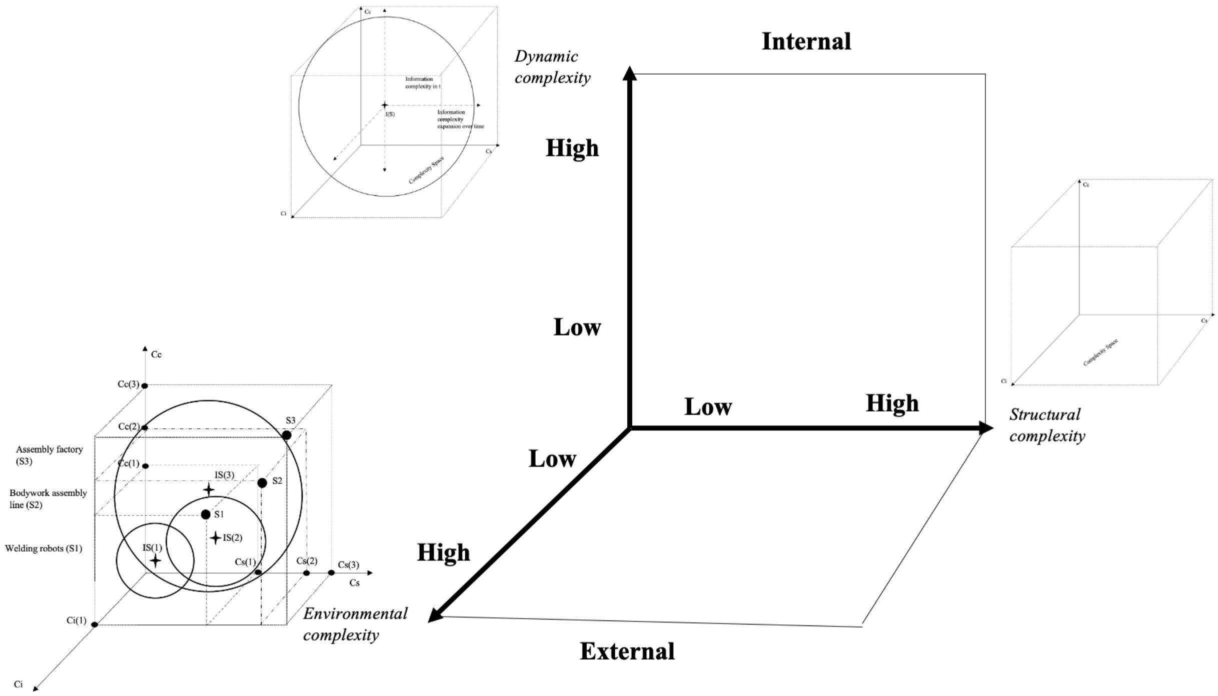



*Figure 85: SCM structure in the context of complexity space*

Figure 85 shows that the SCM structure is based on the proposed complexity space model:

- **Structural SCM dimensions:** Complexity space volume, $V_{Cspace}$
- **Dynamic SCM dimension:** Information complexity sphere *volume* in complexity space, $V_{Sphere}$
- **Environmental SCM dimension:** Multiple system layers in complexity space, $V_{Cspace}$, $V_{Sphere}$ of all system levels.

It is shown that the SCM can be regarded as a coherent derivate of the developed complexity space model and is thus in line with the theoretical assumptions introduced.

The next section now describes the SCM dimension of environmental complexity in more detail.

## 11.3.2 Environmental complexity

In contrast to the other two dimensions, environmental complexity is more difficult to define. It can be stated that environmental complexity shall encompass the relationship of the analysed system to its system external environment and shall refer to how different parts of the system are connected to system exterior elements in the static and dynamic complexity dimensions.

According to Jofre (2020), in the context of business and economic-driven systems three main environments can be identified:

- **Task environment:** All aspects relevant to setting goals and achieving them.
- **Technical environment:** Location where companies produce their products and services.
- **Institutional environment:** Formal rules and beliefs of the company running the system.

It shall be assumed for this dimension, that when the environment of a system is difficult to define and unstable it results a higher degree of uncertainty and complexity, since the overall information that decision-makers must process is complex, fragmented, scarce, difficult to collect or interpret. (Godwyn & Gittel, 2012, Jamshidnezhad, 2015)

In the context of CPS, the system environment can thus be defined as any other system, its components (technical environment), tasks and institutional rules contained which are connected to the system but are outside of the defined system boundary. (Törngren & Grogan, 2018)

This interrelationship now illustrated by the system, where two systems (S1, S2) form a system environment. This is shown in Figure 86.

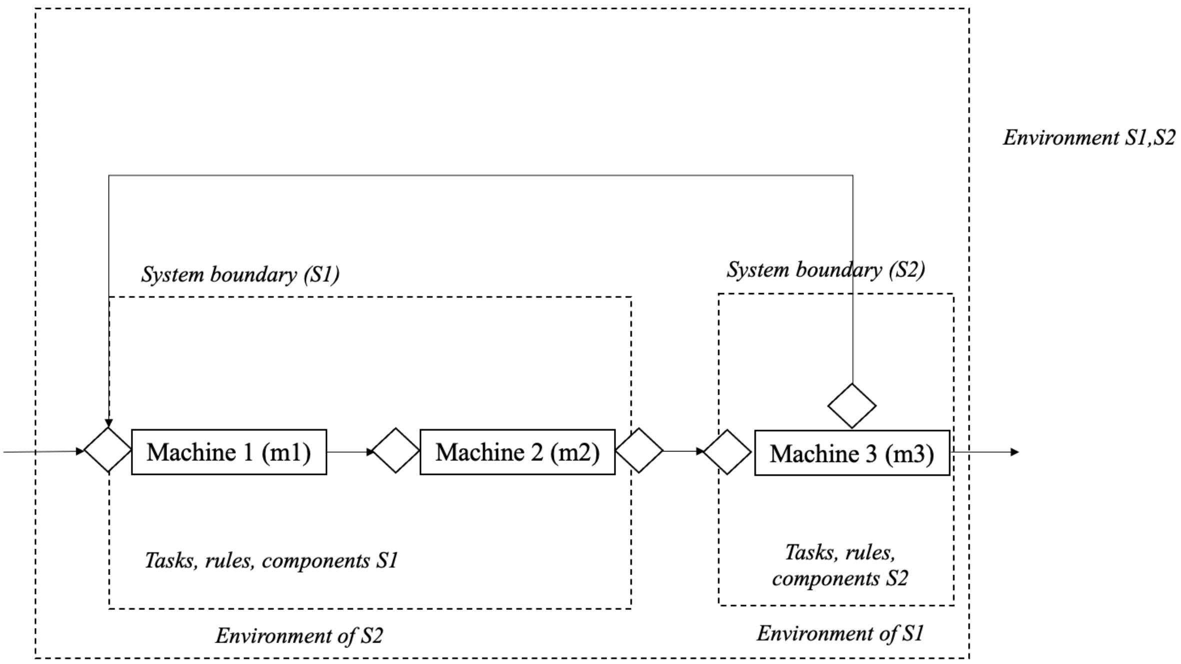



*Figure 86: Environmental complexity*

Overall, it can be stated that the more complex a system´s environment is the more beneficial is the application of a complexity based view for strategic management. (Mason, 2007)

After introducing the complexity dimensions of the SCM in more detail, the next section now discusses the SCM in the context of strategic management perspective.

## 11.4 The SCM in the context of strategic management

Figure 87 now illustrates to which perspective of strategic management the defined SCM complexity dimensions shall be attributed. (Freund et al., 2021)

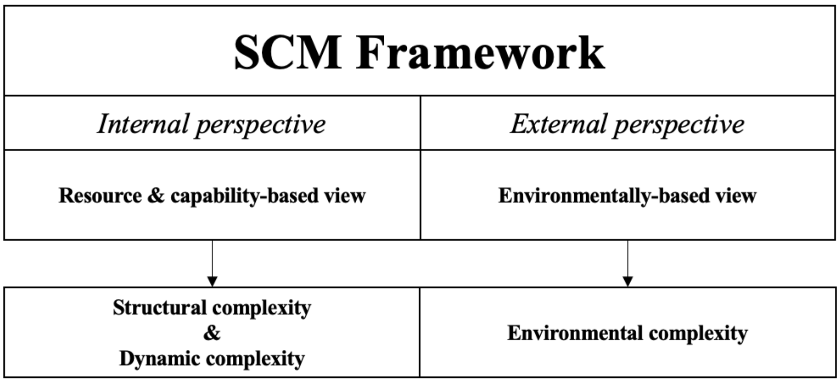



*Figure 87: SCM in the context of strategic management*

Figure 87 shows that the SCM analyses complexity in the two dimensions of strategic management.

This is achieved by assuming the internal and external perspective of strategic management which are attributed with the defined dimensions of complexity.

The SCM thus answers the challenge of the strategy gap in complexity management frameworks by designing a SMTT for complex industrial systems which analyses complexity in the internal and external perspective of strategic management.

The core challenge in this case therefore lies in the premise of the strategic complexity engineering, especially for systems of unprecedented complexity like CPS and CPSS, by establishing a heuristics-based holistic SMTT framework to study complexity in adequate specificity which is at the same time applicable for practice-based use. (Afonina, 2015, Brinzer et al., 2017)

After clarifying how the three dimensions can be attributed in the internal analysis process of the SCM can now be introduced.

### 11.4.1 Internal analysis & classification

Initially, the internal complexity of the analysed system is determined by qualifying the dimensions of structural and dynamic complexity to achieve system classification. It is now possible to summarize all internal system classifications that can result in the SCM.

- **Low/Low:** Complicated system, non-complex, well-understood system.
- **High/High:** Complex system, non-linear, partially random system with strong emergent properties.
- **High / Low:** Structurally complex, structure as main source of complexity
- **Low/High:** Dynamically complex, information as main source of complexity

Figure 88 now expands on this.

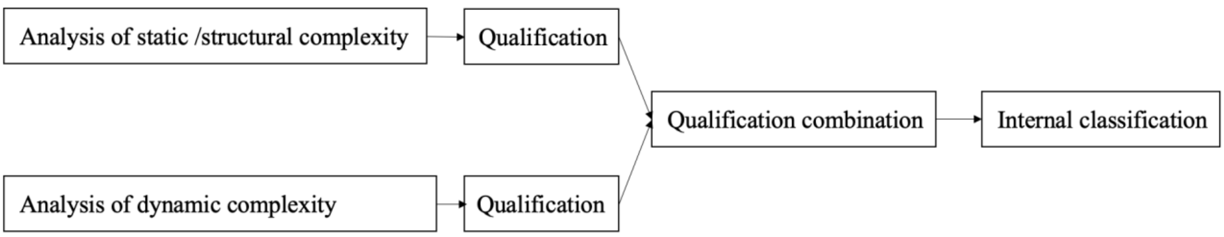



*Figure 88: SCM internal system classification*

Figure 88 now shows that both dimensions are analyzed individually and then combined via qualification combination to achieve an internal classification of internal system complexity.

The next section now covers the external analysis and classification.

## 11.5 External analysis & classification in the SCM

The resulting internal system classification is now applied to the LOW/HIGH qualification of the system external dimension.

For example, a LOW/HIGH dynamically complex system is combined with a HIGH environmental complexity and results in the classification *complex system*.

Figure 89 illustrates all possible outcome combinations.

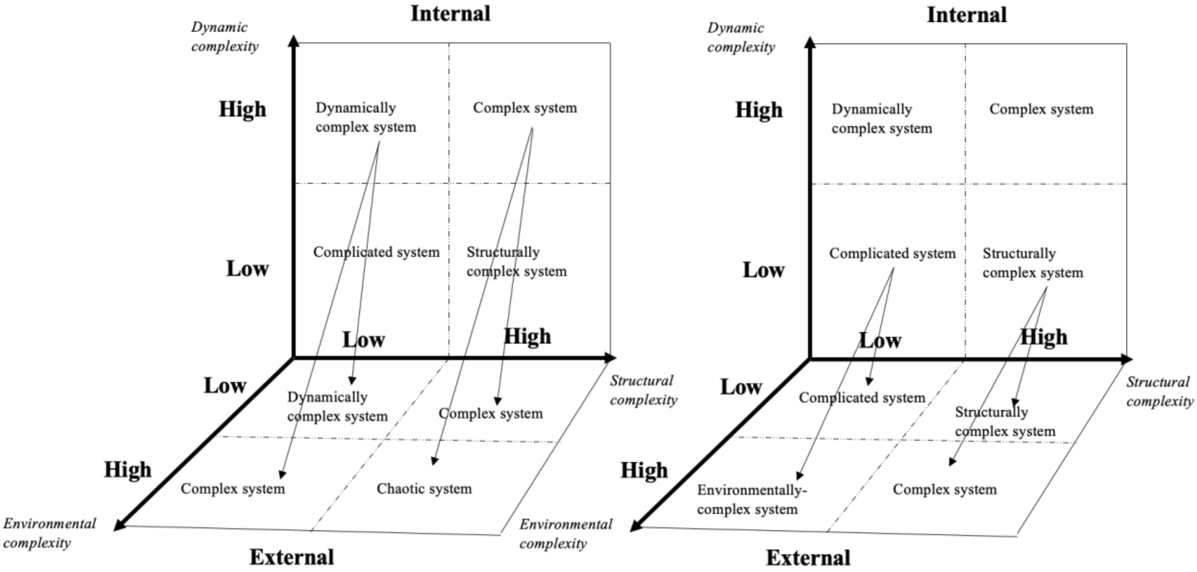



*Figure 89: SCM outcomes*

Overall, it can be stated that a LOW external qualification generally means in the context of the SCM framework that the external environment of the system is clearly definable and is not contributing to uncertainty, while a HIGH external qualification means that the external environment of the system is a major source of uncertainty and is likely to lead to a system of higher complexity classification. (Brinzer et al., 2017, Jamshidnezhad, 2015)

Figure 90 illustrates the external classification process.

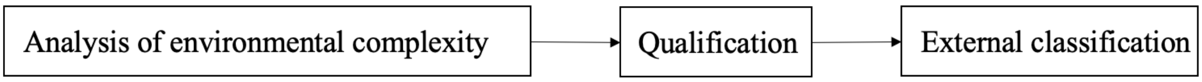



*Figure 90: SCM external classification process*

Figure 90 shows that the analysis of environmental complexity is a linear process of qualification which results in an external classification of environmental complexity. This classification can either manifest in a complicated environment (low) and a complex environment (high).

The next section now covers all possible SCM combinations that can result in the framework.

### 11.5.1 SCM combinations overview

Table 16 now describes all possible SCM combinations.

*Table 16: SCM combinations*

| Classification | Qualification combination (Structural /Dynamic /Environmental complexity) | Description |
|---|---|---|
| Complicated system | Low/Low/Low | Non-complex, well-understood system. |
| Chaotic system | High/High/High | Non-linear, random system, several main sources of complexity in all three dimensions of analysis. |
| Complex system | High/High/Low<br>Low/High/High<br>High/Low/High | Non-linear, partially random system, several main sources of complexity in at least two dimensions of analysis. |
| Structurally complex | High / Low /Low | Structure as main source of complexity. |
| Dynamically complex | Low/High/Low | Information as main source of complexity. |
| Environmentally complex | Low/Low/High | System environment as main source of complexity. |

After expanding on all possible SCM combinations the next section now illustrates and describes the complete SCM process.

### 11.5.2 The complete SCM process

Figure 91 now summarizes the complete SCM process of analysis.

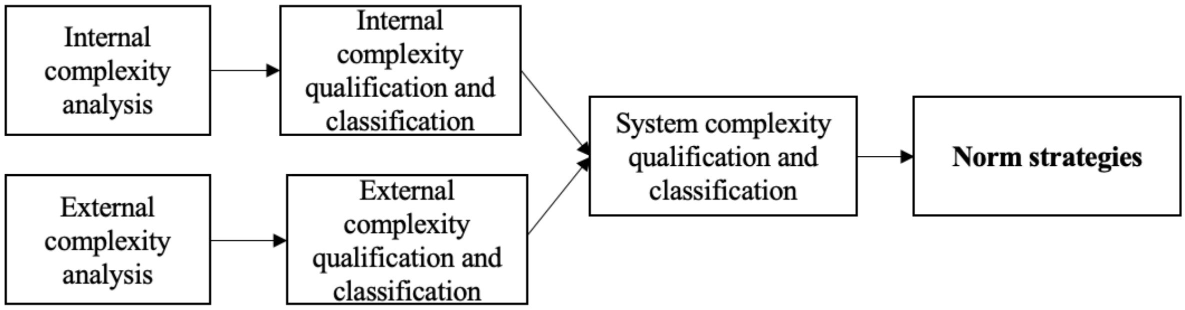



*Figure 91: Complete SCM process*

Figure 91 shows that the SCM is based on two different types of analysis, the internal and external analysis of system complexity.

Both types of analysis lead to their respective system qualifications and classifications which are then combined to the final system qualification and classification.

Table 17 now summarizes each step in the SCM process.

*Table 17: SCM process summary*

| **Step** | **Description** |
|---|---|
| Internal analysis & external analysis | Analysis of structural, dynamic, and environmental complexity dimensions of the system. |
| Internal & external complexity qualification | Low / high qualification of each dimension. |
| System complexity qualification and classification | Resulting final qualification combination and generation of system classification. |
| Norm strategies | Enabling the deduction of norm strategy based on SCM logic and obtained system classification. |

In a next step, it is introduced and explained how the final system qualification and classification is applied to generate norm strategies in the SCM.

To achieve this the next chapter introduces and discusses different complexity management strategies.

## 11.6 Complexity management strategies for the SCM

To react on existing complexity within the mentioned complexity dimensions, different strategies can be developed and can be applied. These strategies can aim either at manipulating the complexity or at coping with the existing complexity. Based on Kluth et al. (2014) and Lindemann et al. (2009) three general strategies, *norm strategies*, of complexity management can be distinguished in the context of the SCM.

These strategies are now described in Table 18.

*Table 18: SCM norm strategies*

| **Strategy** | **SCM norm strategy** | **Description** |
|---|---|---|
| Avoiding complexity | **Avoid** | Prophylactic prevention of the emergence of complexity. The reappearance of over-complexity must be prevented by proactive use of instruments. These include, for example, the modularization, standardization or outsourcing of products, processes, or organizational structures or even total the replacement of a system in extreme cases. |
| Reducing complexity | **Manage** | Complexity reduction is about reducing identified existing complexity. This can be achieved by the reduction of variety and heterogeneity. This means by achieving the simplifications in the various fields of complexity. This includes, for example, the elimination of unprofitable product variants, the reduction of non-value-added process steps, the reduction of interconnection, information flow, information amount as well as the reduction of interfaces. |
| Dealing with complexity | **Identify** | The dealing with complexity is aiming at the efficient coping with unavoidable complexity. This includes the identification of complexity, the increase of process transparency or transformation of the processes to avoid hidden complexities. |

The next section now shows how these strategies can manifest in the SCM via norm strategies.

### 11.6.1 SCM norm strategies

Based on the provided strategies and after achieving system qualification and classification in the SCM a first set of norm strategies for the SCM in the form of *identify, manage,* and *avoid* can now be introduced.

These norm strategies are put into the context of the SCM as described in Figure 92.

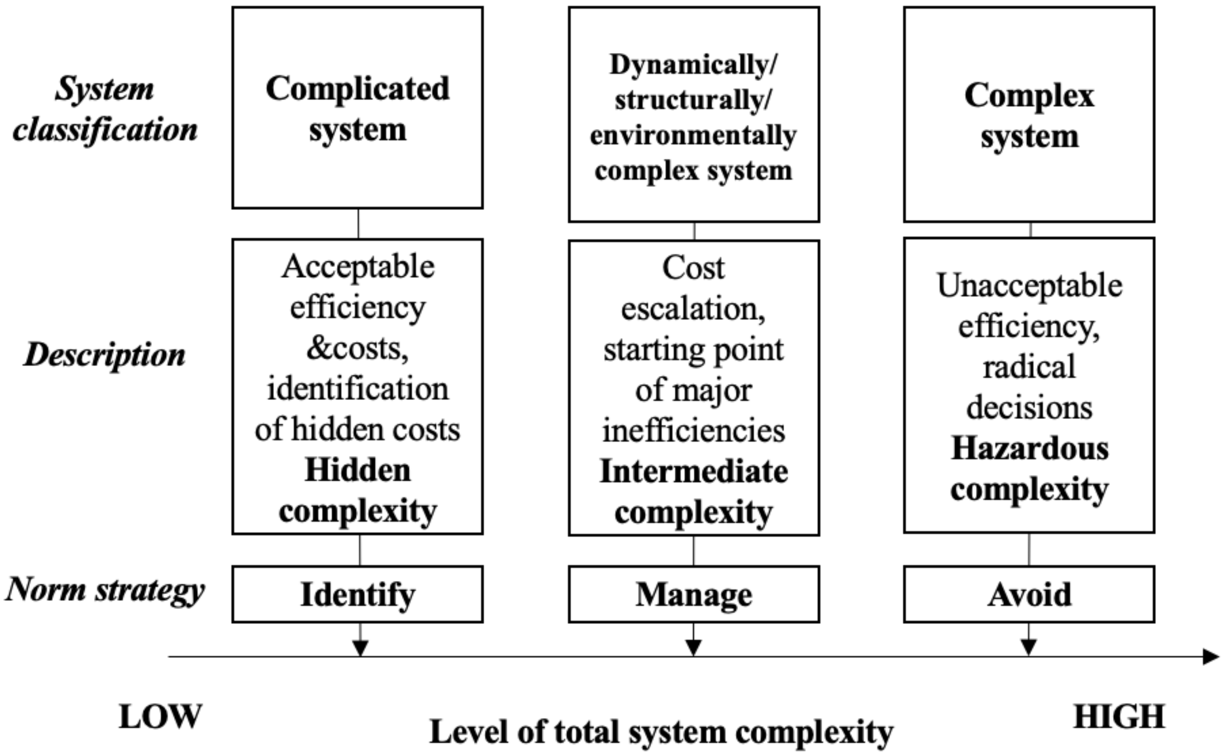



*Figure 92: SCM norm strategies*

Figure 92 shows that the SCM attributes the defined three different norm strategies in relation to the level of the overall system complexity. The level of the overall system complexity is furthermore corresponding to the obtained SCM qualifications and resulting system classification.

This allows to coherently deduct the fitting norm strategy to each system analysed via the SCM analysis.

To illustrate the mechanics of the SCM the next section now provides an example.

## 11.7 How the SCM works

To illustrate the mechanics of the SCM, a given hypothetical system shall be defined by the following properties as shown by the SCM matrix in Figure 93.

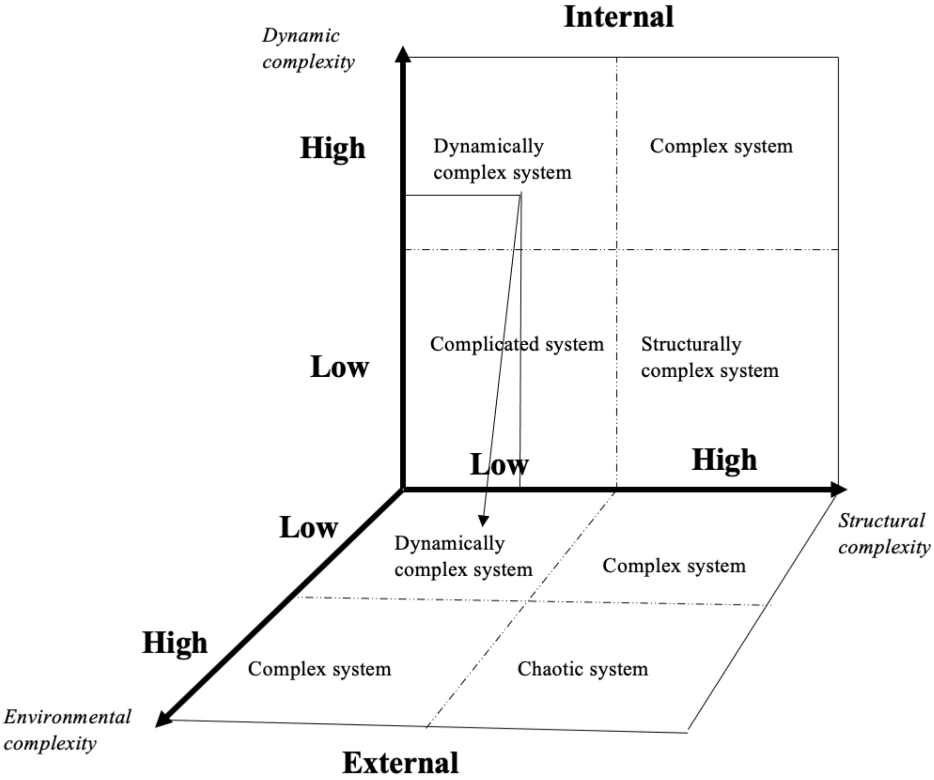



*Figure 93: SCM example application*

The provided SCM matrix in Figure 93 shows that the system shall be classified as a dynamically complex system.

The underlying process of analysis can now be defined as the illustrated in Figure 94.

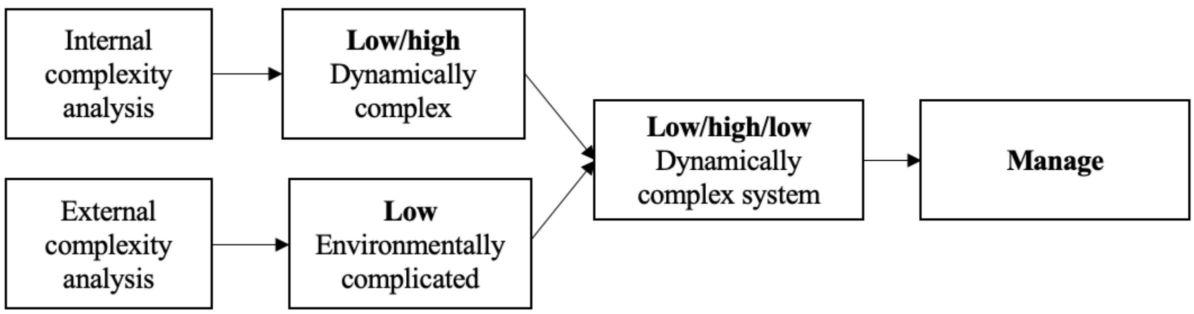



*Figure 94: SCM example analysis*

Based on this result, the generated norm strategy for the dynamically complex system can be defined in more detail in Figure 99.

Figure 95 now illustrates the meaning of a generated norm strategy as an indicator for system complexity and how to deal with it.

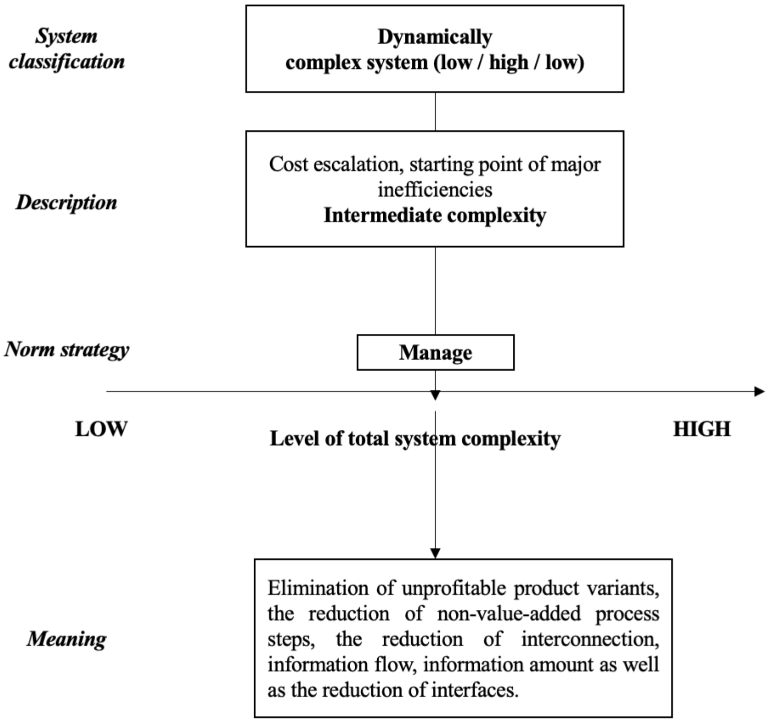



*Figure 95: SCM practical meaning of norm strategies example*

Figure 95 shows that a given analysed case can now be coherently interpreted in the context of the provided norm strategy *manage* and a first starting point to optimize the analysed system is provided due the potential practical meaning of the norm strategy. The norm strategy thus refers to several practical measures which could be implemented to avoid cost escalation and other major inefficiencies.

Due to the SCM analysis it is now also clearly defined how complex the system is in general, what the dimensional source of complexity in the system is and in which dimension the practical measured would have to be implemented to achieve increased system performance and therefore creates a holistic system strategic vision of how to improve the system. (Knyazeva, 2020) The provided example illustrates that the SCM represents a holistic SMTT that coherently allows the classification of complexity in manufacturing systems and the development of norm strategies to enable decision-aiding.

In the light of this statement, the next section now further discusses the SCM in the context of the applied decision-aiding methodology to further validate the SCM structure and mechanics.

## 11.8 SCM implications for application

To summarize, it is now possible to draw the following implications for the practical instrumental value of the SCM:

- A strategic complexity framework in the form of the SCM framework is proposed. The SCM framework functions as a practice based SMTT, a SMTT for complexity analysis of current and future complex industrial systems, like CPS.
- The dimensions of the model in the form of structural, dynamic, and environmental complexity are introduced and described.
- The core capabilities in the form of system qualification, classification, and norm strategies of the SCM framework are theoretically demonstrated.

The mentioned implications show that the proposed SCM framework achieves its primary goals of theoretically enabling strategic complexity management while serving as a SMTT to solve problems of complexity in a practical engineering decision-making context.

The SCM complexity dimensions, structural, dynamic, and environmental, as well as the framework's strategic capabilities are theoretically demonstrated based on a set of generic norm strategies and illustrates via an example analysis.

SRQ3 can now be answered.

- ***Sub-research question 3 (SRQ3; O3):*** **How can a strategic complexity management framework for industrial systems be coherently established?**

  ***Answer:*** Based on the integration of the complexity dimensions structural, dynamic, and environmental complexity in a holistic SMTT, a strategic complexity management framework for industrial systems is coherently established in the form of the SCM.

After answering SRQ3 and achieving the corresponding objective O3, the next chapter now presents the applied SCM case study method in more detail.

# 12 SCM applied case study method

Building on the described structure and functioning of the SCM in the previous chapter and the defined methodology in Chapter 8, this chapter now describes in detail how the SCM is applied on real-world industrial systems.

As stated in O4, the final objective of this thesis is to investigate the practical applicability of the SCM framework on real-world production systems. This chapter thus also has the goal to adhere to axiom A3: *managing complexity*.

To achieve this the SCM framework is executed four times, resulting in four individual case studies of real-world industry systems.

This results in four systems which are analysed in the context of the research question to explore and investigate the applicability of the SCM on real world decision-making problems in the area of complexity in industrial systems.

As already established in Chapter 8 and based on the complex system multi-case study research displayed in Gorod et al. (2014), the role of the researcher is that of an interpretative analyst in the decision-aiding process for a given company / client and thus is directly involved in the SCM projects through interventionist research.

Therefore, all the cases are executed while the researcher and the company are being positioned in an interventionist client / analyst relationship process of decision-aiding.

Consequently, the results and learnings of each SCM project are produced by the author of the thesis in the respective analyst role and thus represent exploratory, subjective results.

Based on Chapter 8, the following Table 19 gives an overview about the relevant elements of case-study based research for the SCM case studies and provides a more detailed description.

*Table 19: SCM case study elements*

| **Element** | **Description (Case specific)** |
|---|---|
| Unit of analysis | Application of SCM on industrial manufacturing system of two different companies in Austria and Hungary. |
| Selection criterion | Industrial manufacturing system poses a complex decision-making problem to senior decision-makers. |

| | |
|---|---|
| Data collection process | Companies provide a set of documents as the primary information source. |
| Collecting the data (forming the database) | Information sources include:<br>I. Project documents (factory layouts)<br>II. Project reports, including quarterly reports, midterm review<br>III. Calculations<br>IV. Facility assessment reports<br>V. Maintenance reports and others (videos etc.) |
| Analyzing the data | Document review & analysis process + application of SCM |
| Interpretation of data / SCM analysis | Interpretation of results of SCM with the aim to generate norm strategy for individual case. |

In reference to Chapter 8, Figure 96 now illustrates how each case is approached from a methodological standpoint by integrating the SCM into the decision-aiding process.

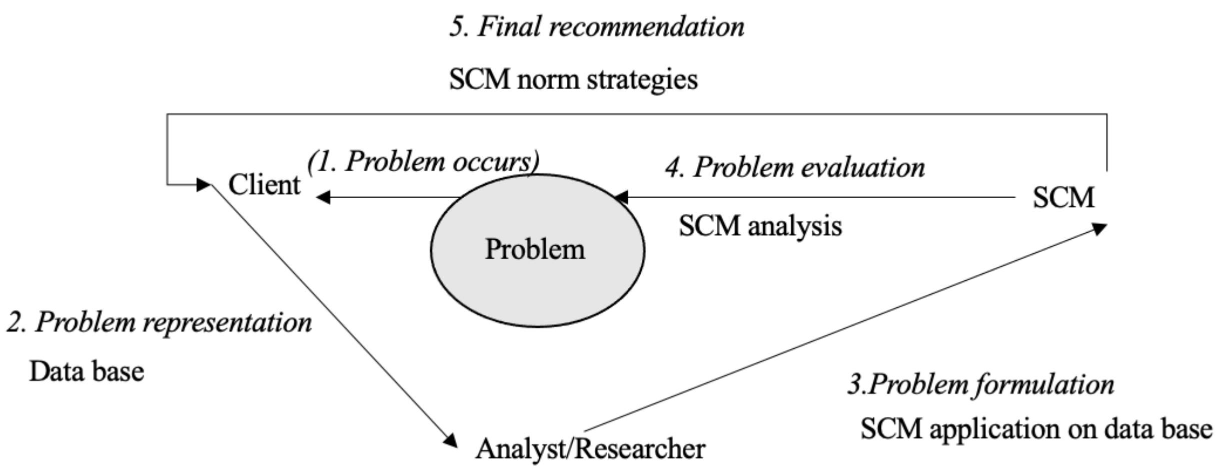



*Figure 96: SCM case studies in the context of decision-aiding*

Figure 96 shows that in the conducted case study research the researcher has been positioned in the analyst role with the goal of achieving problem formulation, problem evaluation and the generation of a final recommendation while drawing on a data base.

The next section now introduces and describes the SCM case study design in detail to provide further information on the concrete utilization of the SCM in the conducted case studies and how knowledge is obtained from methodological standpoint.

## 12.1 Case study design

Based on Campbell et al.  (2018) and in correspondence to Chapter 8, Figure 97 now provides an overview about the general applied case study structure for an individual case.

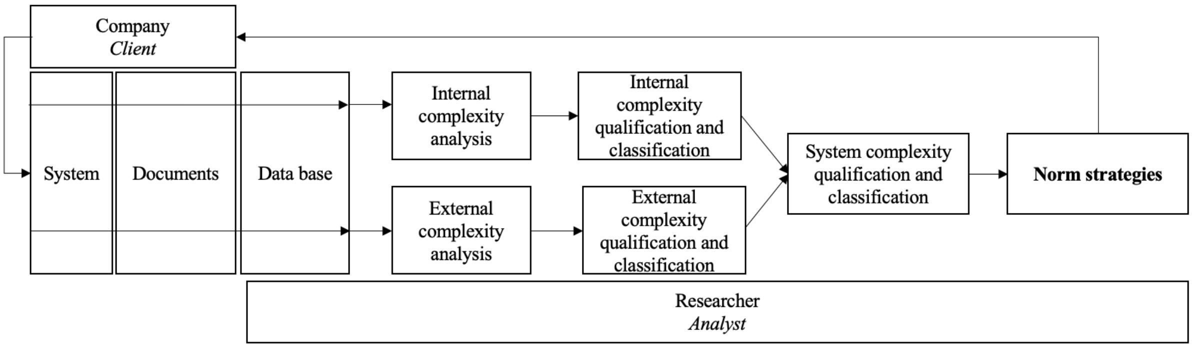



*Figure 97: SCM case study design*

Figure 97 shows that the domain of the client, the company, is defined as the system to be analysed and the documents provided to the analyst / researcher by the company which then form a database for the analyst / researcher to apply the SCM on.

The domain of the researcher in the role of the analyst is the establishment of the data base and the application of the data to achieve internal and external complexity analysis for the SCM, which then leads to the generation of system complexity qualification and classification and the respective norm strategy as the result.

The norm strategy is then reported back to the company / client, who can then choose to implement the strategy on the system or not.

In theory, this would allow a second application of the SCM on new system documents which reflect the changes implemented to allow benchmarking over time in the form of a longitudinal case study for further research. It is important to mention, that this is not a part of the shown research.

The next section now describes in more detail how the resulting multi-case study approach can be defined for the SCM application.

### 12.1.1 Multi-case study approach

Based on Campbell et al. (2018) and in correspondence to Chapter 8, the applied multi-case approach for the SCM is illustrated by Figure 98.

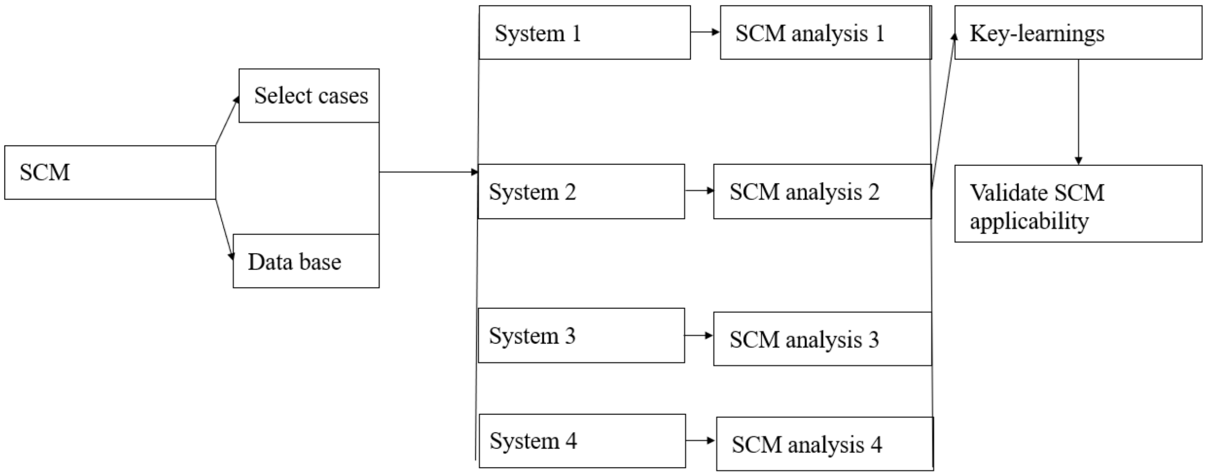



*Figure 98: SCM multi-case study approach*

Figure 98 shows that the chosen multi-case study approach is based on the analysis of four different manufacturing systems, which represent four isolated case studies. These case studies encompass the respective SCM analysis for the individual case.

The SCM is thus applied to each system individually via an established database, leading up to four individual and separate SCM analyses conducted by the researcher.

Each analysis contains therefore its own isolated learnings and conclusions regarding the applicability of the SCM on the respective system.

In a next step these conclusions and learnings of the individual SCM analysis are generally compared and discussed to achieve key-learnings concerning the general applicability of the SCM on industrial systems.

Based on this process the next chapter now defines how the case data base is established and analysed via the researcher in the context of the SCM via qualitative document review and analysis (QDA).

The next section now describes the applied QDA procedure in more detail.

## 12.2 Data analysis method: qualitative document review & analysis

Qualitative document review and analysis (QDA) describes a qualitative, systematic procedure for reviewing or evaluating documents, printed and electronic (computer-based and internet-transmitted) material, which then can provide data on the research context, for example in the form of background information or historical insight.

This aspect is especially important for events that cannot or no longer be directly observed. (Bowen, 2009, Wach, 2013)

The core understanding of QDA for this thesis is established by Bowen (2009) as the process of evaluating documents in such a way that empirical knowledge is produced, and understanding is developed.

The documents that were used for systematic evaluation as part of the data base of the presented case studies were provided by the partner companies and take a variety of forms, for example factory layouts, calculations, or maintenance reports.

Figure 99 now illustrates the general concept of QDA for this thesis, based on Altheide & Schneider (1996), Wach (2013) and Bowen (2009)

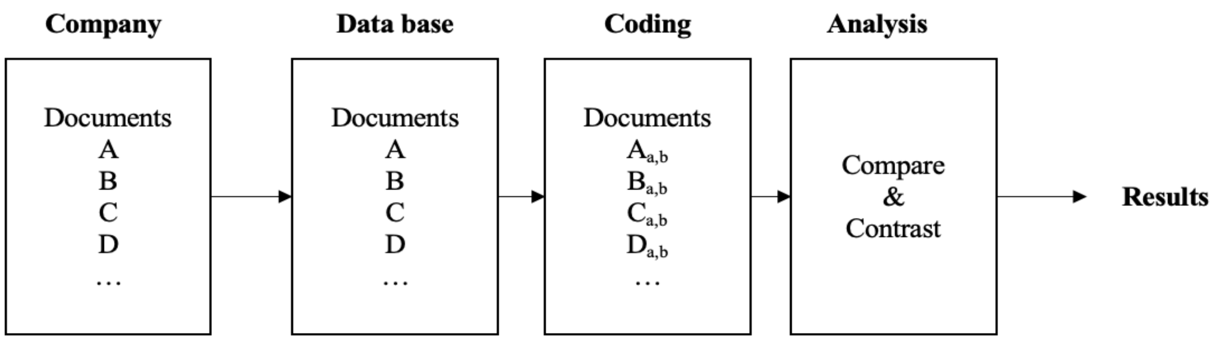



*Figure 99: QDA process of SCM case studies*

Figure 99 shows that the QDA process consists out of four different steps, which entail the company providing the documents, document storage in a data base, document coding and analysis.

The next section now describes the procedure of QDA in more detail.

### 12.2.1 SCM QDA procedure

Based on Wach (2013) and Altheide & Schneider (2013) the QDA contains the following steps as described in Table 20.

*Table 20: QDA procedure*

| **Step** | **Description** |
|---|---|
| Setting inclusion criteria for documents | • Included organizations<br>• Types of documents to be reviewed |
| Collecting documents | • Inside the organization (internal) |
| Articulating key areas of analysis | • SCM dimensions |
| Document coding | Each document was analyzed to determine the extent to which the SCM complexity dimensions are described, addressed or considered each of the identified themes or dimensions via a document analysis taxonomy. |
| Verification | To ensure consistency and reliability of the coding and assessment process, the analysis of every document was verified by the research team. |
| Analysis | This data was then analyzed via thematic analysis to determine the results of each case study via the SCM and generates a norm strategy. |

The next section now describes the first step of QDA, namely the SCM analysis inclusion criteria.

### 12.2.2 SCM analysis inclusion criteria

The following inclusion criteria were applied to select the partner companies for the SCM case studies.

- Company is a manufacturer in Europe.
- Senior management of company wants to address a relevant problem of complexity concerning a production system with the help of SCM analysis.
- Company can provide electronic documents for analysis.

The next section describes the step of document collection in the data base.

### 12.2.3 Collecting documents

The chosen case study design allows to achieve the following principles of data collection to contribute to the validity and reliability of the study as well as rigor and thoroughness in the case study process. (Bowen, 2009)

- Multiple sources of evidence in the form multiple document types
- Database creation
- Maintaining a transparent chain of evidence in the SCM analysis process.

In total, 44 computer-based and internet-transmitted documents of various types collected in the database were individually reviewed by research team and applied to the three different dimensions of the SCM in nine different document type categories. The following Table 21 now displays the distribution of document types in the generated database and the attributed complexity dimensions for analysis in the SCM.

*Table 21: SCM case studies document database*

| **Document Type** | **Amount** |
|---|---|
| Production schedule | 17 |
| Cost calculations | 3 |
| Shop floor layouts | 2 |
| Maintenance procedures | 10 |
| Quality management | 5 |
| Material treatment | 2 |
| Operating procedures | 1 |
| Supply chain | 2 |
| Other (videos etc.) | 2 |

It is shown that the received 44 documents are distributed among 9 different types of documents, with the type of *production schedule* having the highest number of documents received (39%).

The next section now covers the step of how key areas of analysis are defined for the QDA of the SCM case studies.

### 12.2.4 Articulating key areas of analysis

To allow a consistent and coherent application of the SCM on a given set of data base documents, an interpretative scheme of analysis key-areas which are applied to achieve problem formulation is introduced through the three dimensions of complexity analysed by the SCM in Table 22.

*Table 22: QDA key areas of analysis*

| **Key-area** | **Description** |
|---|---|
| Structural complexity<br>(S) | Document primarily refers to the static architectural layout of the system. For example:<br>• Amount of machines<br>• Number of links between machines<br>• Number of interfaces |
| Dynamic complexity<br>(D) | Document primarily refers to the amount of information contained and circulated in the system in terms of information entropy. For example:<br>• Random system breakdowns<br>• Random system errors<br>• Deviating system behavior<br>• Flow of material/information |
| Environmental complexity<br>(E) | Document primarily refers to:<br>• Task environment (all aspects relevant to setting goals and achieving them)<br>• Technical environment (location where companies produce their products and services)<br>• Institutional environment (formal rules and beliefs of the company) |

After presenting the key areas of analysis, the section to follow now introduces the chosen document coding approach.

### 12.2.5 Document coding approach

The goal of the document coding process is defined by Bowen (2009) as organizing the information into a structure that provides knowledge about what is related to central questions of research. Figure 100 now illustrates the applied complexity scope taxonomy for multi-level document coding in the context of the dimensions of the SCM.

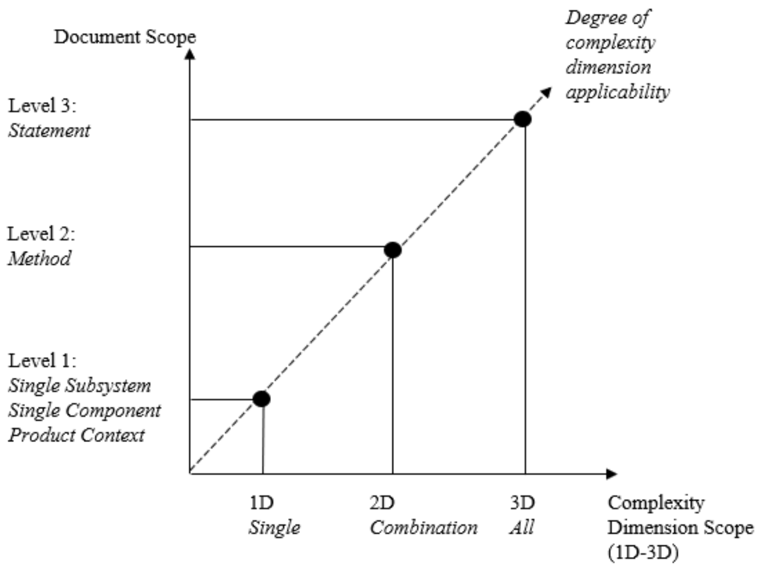



*Figure 100: SCM document coding taxonomy*

The applied taxonomy is based on the Taxonomy Dimensions of Complexity Metrics described by Falah & Magel (2015).

As a next step, the SCM taxonomy scope levels are defined in more detail in the next section.

The individual document scope levels can now be defined as the following:

- **Level 1:** Provides insight into a single-subsystem (production step), component (intermediate product) or provides product context (list of product parts).
- **Level 2:** Provides insight into an applied method (quality management procedures, material treatment procedures, maintenance procedures, supply chain).
- **Level 3:** Provides insight into an overall body of knowledge that encompasses the whole system (production schedules or cost calculations).

It is shown that documents are evaluated based on the level of insight they can offer in the three complexity dimensions of the SCM in which they are to be interpreted and analysed.

The next section now provides document and document scope examples for each level to illustrate how the applied SCM taxonomy works.

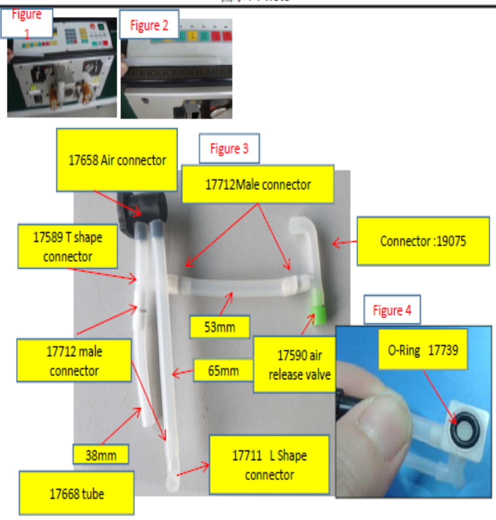
### 12.2.6 Document and document scope illustration

Based on the described document scope levels, obtained real-world original documents can now be provided to illustrate the approach. Figure 101 now illustrates a Level 1 document in the form of a standard operation procedure for a rubber tube assembly.

| 工序号 Station No. | BM28_Sarah-010 | 工序名称 Procedure Name | Rubber Tube Assembly | 标准时间 Operation Time | 20" |
|---|---|---|---|---|---|

| | Step |
|---|---|
| 1 | Take a roll of rubber tube and put them onto the automatic tube cutting machine.(figure 1) |
| 2 | Adjust the parameters of the machine, on the switch, start automatic rubber cutting.(figure 2) |
| 3 | Rubber tube cutting machine parameter：L=53mm L=38mm L=65mm |
| 4 | Take the sealing ring, install it on the air connector.(figure 4) |
| 5 | Assemble the tee connecting tube, rubber tube and silicone connecting tube (figure 3) |
| 6 | Check whether the rubber tube assembly is wrongly installed, reversed or missing. |

图示 / Photo




| | Attention |
|---|---|
| 1 | Check that the assembled tube must not be broken. |
| 2 | The parameters of the automatic tube cutting machine shall be adjusted by specialized personnel. |
| 3 | Adjust the parameters of the tube cutting machine according to the user manual. |
| 4 | Do a tube cutting test with 10 pcs before the mass production. |
| 5 | Check 1-2 times per hour to check whether the length of the tube cutting is accurate. If it is inaccurate, adjust the parameters again |

| Part Description | | | | | 使用工/夹具 / Jig / Fixture Description | | | |
|---|---|---|---|---|---|---|---|---|
| 序号 Item | 物料名称 Part Des. | 物料编号 Code | 规格 Specification | 数 量 Qty | 序号 Item | 工/夹具名称 Jig / Fixture Description | 规格 Specification | 数量 Qty |
| 1 | T shape connector | 17589 | N/A | 1个 | 1 | Tube cutting machine | N/A | 1台 |
| 2 | Slowly air release valve | 17590 | N/A | 1个 | 2 | Box | Red | 1个 |
| 3 | Air connector BPM | 17658 | N/A | 1个 | 3 | Box | Blue | 1个 |
| 4 | O-ring | 17739 | 4.6×8.2 d1.8 | 1个 | 4 | | | |
| 5 | Silicone connector | 17711 | D5x2.5 | 1个 | 5 | | | |
| 6 | F shape connector | 19075 | N/A | 1个 | 6 | | | |
| 7 | Tube | 17668 | L=54mm,38mm，63mm | 共3个 | 7 | | | |
| 9 | Male connector | 17712 | N/A | 4个 | 9 | | | |
| 10 | | | | | 10 | | | |

*Figure 101: Level 1 document*

Table 23 describes the displayed Level 1 document in more detail.

*Table 23: Level 1 document description*

| **Document detail** | **Description** |
|---|---|
| Name | Rubber tube assembly |
| Context | Part assembly instruction |
| Scope | Level 1 |
| SCM dimensions | (D) since it refers to the information / material flow in the system. |

The next section provides an example for a Level 2 document.

Figure 102 illustrates a Level 2 document in the form of a 5S-Audit manual.

| [redacted] | **AA 075 – 5S-Audit** | Seite 1 / 2 |
|---|---|---|

***Ziel und Zweck:***

Diese Arbeitsanweisung regelt die Durchführung und den korrekten Ablauf von Betriebsbegehungen hinsichtlich Sicherheit, Ordnung und Sauberkeit. Diese Begehungen werden im Haus allgemein als 5S bezeichnet.

***Geltungsbereich:***

Diese Anweisung gilt für die komplette Organisationseinheit (ausgenommen Office und KB)

***Allgmeines***

Was bedeutet 5S?

**Seiri** - Sortiere aus. Alles was für die Arbeit an diesem Platz nicht benötigt wird, aussortieren.

**Seiton** - Stelle ordentlich hin. Was tatsächlich gebraucht wird, bekommt einen unter ergonomischen Gesichtspunkten ausgesuchten, definierten und gekennzeichneten festen Platz.

**Seiso** - Säubere. Der Arbeitsplatz wird von Grund auf gereinigt.

**Seiketsu** - Sauberkeit bewahren. Das bedeutet stetiges Aufräumen und verhindert, dass neue Gegenstände ungeplanten Zugang zum Arbeitsplatz finden.

**Shitsuke** - Selbstdisziplin üben. Damit Ordnung und Sauberkeit aufrechterhalten werden, ist Disziplin erforderlich. Ist eine Stellfläche für ein Werkzeug definiert, gehört es auch dahin – immer.

***Durchführung:***

Die 5S-Audits werden quartalsweise durchgeführt, anhand der Checkliste „5S Liste". Diese Liste wird jährlich neu erstellt und im Ulysses in der Projektverwaltung unter PM 3500-3 „Protokoll 5S-Audit" und dem jeweiligen Jahr abgespeichert, sowie mit Passwort geschützt.

*Figure 102: Level 2 document*

Table 24 describes the displayed Level 2 document in more detail.

*Table 24: Level document description*

| **Document detail** | **Description** |
|---|---|
| Name | AA 075-5S Audit |
| Context | Instruction to clean the system according to 5S method and how the system shall be managed and maintained. |
| Scope | Level 2 |
| SCM dimensions | (D) and (E), refers to information flow, unwanted system behavior and task, and informal environment of the analysed system. |

The next section now provides an example for a Level 3 document.

Figure 103 illustrates a Level 3 document in the form of material and labor cost calculation.

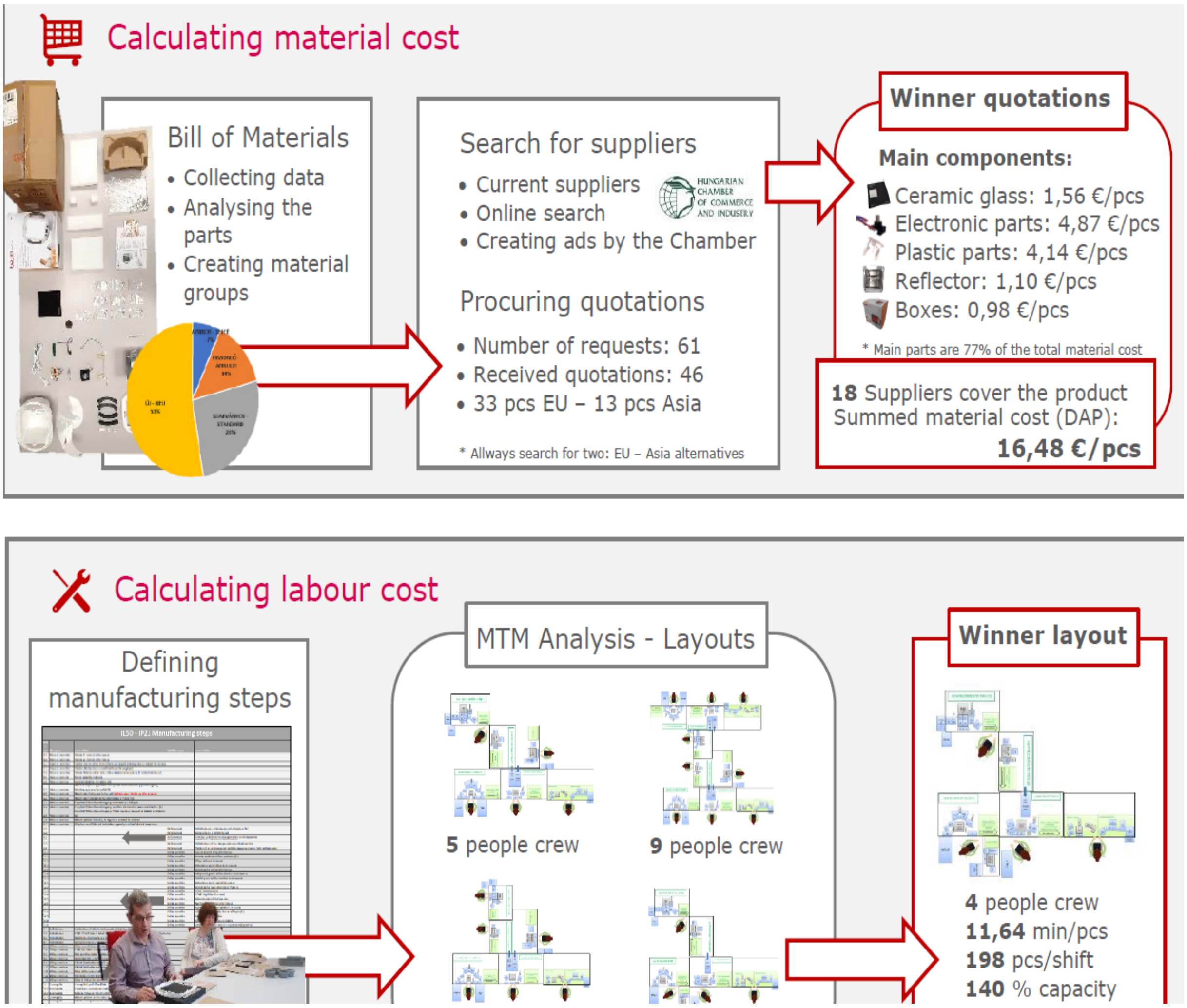



*Figure 103: Level 3 document*

Table 25 describes the displayed Level 2 document in more detail.

*Table 25: Level 3 document description*

| Document detail | Description |
|---|---|
| Name | Material and labor cost calculation via Methods-Time-Measurement and material cost analysis. |
| Context | Definition of layout and component cost composition. |
| Scope | Level 3 |
| SCM dimensions | (S) (D) (E). Refers to all dimensions, since system architecture, dynamics, and system environment (supply chain) are described and illustrated. |

The next section now elaborates on how the verification of the coding.

### 12.2.7 Verification of coding

During the SCM process the classification of the individual documents in terms of scope and type was regularly discussed with other members of the research team as well as the senior management of the company providing the documents to avoid errors and misjudgments.

## 12.3 Document coding: results

The distribution of received documents among complexity dimensions of the SCM based on the SCM taxonomy is now defined as the following Table 26.

*Table 26: Document coding results*

| Document Type | Complexity dimensions | Taxonomy scope | Taxonomy reasoning | Amount |
|---|---|---|---|---|
| Production schedule | Dynamic, Environmental, Structural | Level 3 | Statement | 17 |
| Cost calculations | Dynamic, Environmental, Structural | Level 3 | Statement | 3 |
| Shop floor layouts | Structural | Level 1 | Single Sub-Systems, Product Context | 2 |
| Maintenance procedures | Dynamic | Level 2 | Method | 10 |
| Quality management | Structural, Dynamic | Level 2 | Method | 5 |
| Material treatment | Structural, Environmental | Level 2 | Method | 2 |
| Operating procedures | Structural, Dynamic | Level 2 | Method | 1 |
| Supply chain | Environmental, Dynamic | Level 2 | Method | 2 |

|  |  |  |  |  |
|---|---|---|---|---|
| Other (videos etc.) | Dynamic, Environmental, Structural | Level 1-Level 3 | Misc. | 2 |

The shown distribution of document types on SCM dimensions is based on the specificity, purpose, and the contextual richness of the individual document in the individual dimension according to the defined document scope level in the applied taxonomy. (Bowen, 2009)

For example, documents of the type of *production schedule* have shown to provide relevant insights into all SCM dimensions, since the reviewed documents of this type were connecting most relevant aspects of production in the production schedule.

On the other hand, documents of the type of *shop floor layouts* and *maintenance procedures* are highly specific in their individual nature and can thus only be applied to a singular dimension of analysis.

The described document review and analysis process therefore establishes a clear chain of evidence explicitly linking the data collected, the framework applied, and the conclusions drawn from the SCM in a logically coherent, reliable, replicable with high validity. (Kaman & Othman, 2016)

The resulting distribution of documents among the document scope level of the taxonomy can now be illustrated in Figure 104.

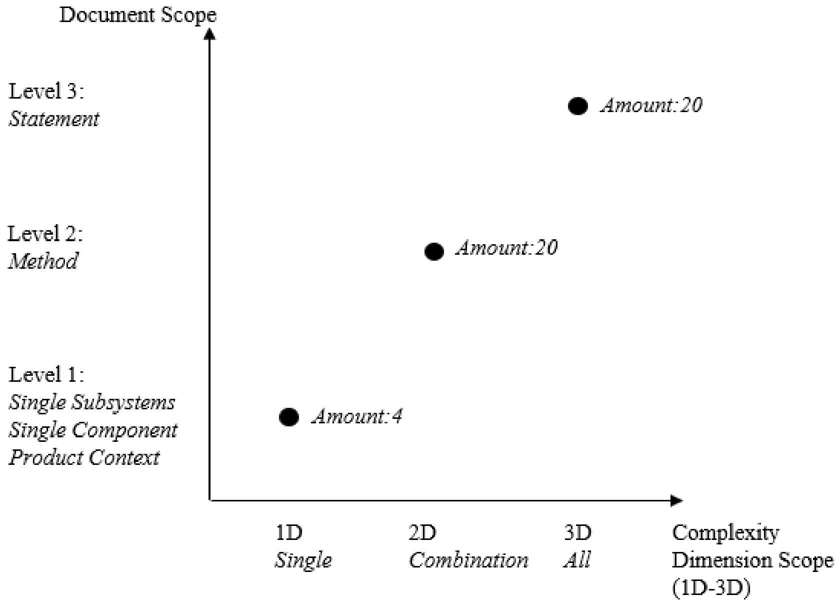



*Figure 104: Received document distribution in taxonomy*

The provided SCM taxonomy allows to classify database documents in a coherent way to achieve SCM applicability via the S,D,E complexity dimensions.

It can be shown, that 40 out 44 documents are Level 2 or Level 3 documents, while only 4 of the 44 received documents are Level 1 documents, underlining the contextual richness of the database for the conducted SCM analysis making the data base suitable for heuristic SCM analysis.

### 12.3.1 Analysis and interpretation of documents

After the document coding process, the documents are interpreted via manual thematic analysis in the context of the SCM.

Thematic analysis in QDA shall be considered a form of pattern recognition with the document's data. The analysis takes emerging themes and makes them into categories used for further analysis. It includes careful, focused reading and re-reading of data, as well as coding and category construction. (Bowen, 2009) The interpretative process is both recursive and reflexive as the researcher / analyst moves between concept development, sampling, data collection, data analysis and interpretation. QDA is thus defined as an open-minded, creative, subjective, and emergent process focused on the search for underlying meanings, themes, and patterns, rather than a rigid set of procedures with tight parameters. Consequently, it is to be expected that the results are significantly impacted by the researcher's subjective perspective. (Wood et al., 2020)

Thematic analysis in the context of the SCM therefore means that the coded documents are now interpreted via a baseline interpretation scheme in the different a priori SCM dimensions to allow the qualification high / low in the matrix.

This achieves a guided, semi-open approach, that avoids the fully open approaches like brainstorming or mind maps which would be used in a less a priori way of open data exploration and interpretation.

This then leads to a more stringent analysis and interpretation that avoids the pitfalls of a "garden path analysis" which is characterized by the exploration of attractive themes that leads potentially nowhere. (Wood et al., 2020)

To prepare for the analysis and interpretation process, the documents were read concurrently as data collection progressed, to develop familiarity with the data and document structures.

Due to the novelty of the SCM as a strategic complexity management framework the applied heuristic interpretation scheme is defined as illustrated in Figure 105.

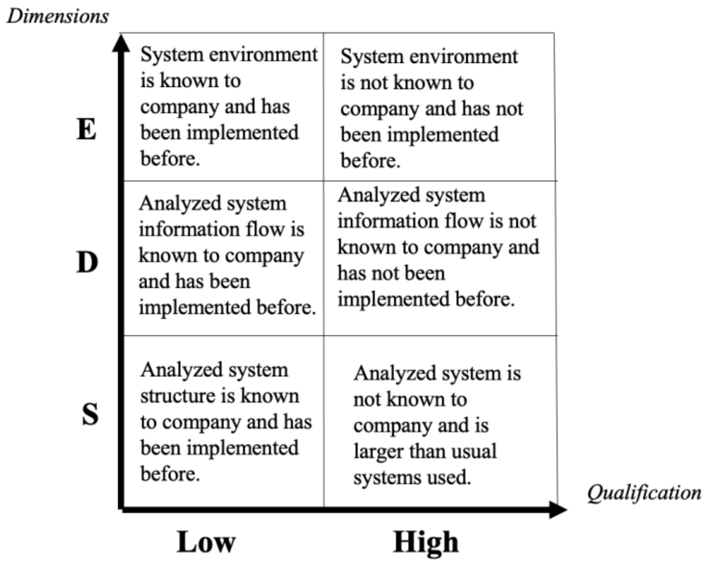



*Figure 105: Document heuristic interpretation scheme*

The provided interpretation scheme represents a set of conclusions for interpretative analysis in the key areas of analysis and shall therefore be a heuristic baseline framework that initially guides the subjective SCM qualification process conducted by the researcher in the client / analyst constellation.

To summarize, there are many benefits in using document analysis for the purpose of this study.

According to Bowen (2009) these are benefits can be defined as the following.

- Document analysis is an efficient and effective way of gathering data because documents are manageable and practical resources.
- Documents are commonplace and come in a variety of forms.
- Obtaining and analyzing documents is cost efficient and time efficient.
- Documents are stable, non-reactive data sources, meaning that they can be read and reviewed multiple times and remain unchanged by the researcher’s influence or research process.
- Documents can also contain data that no longer can be observed, provide details that informants have forgotten, and can track change and development.

After presenting the method and benefits of QDA for SCM analysis, the next section discusses the limitations of QDA.

## 12.4 QDA limitations

The following limitations for QDA can be identified and must be considered at any time in the context of the results of the case study application of the SCM. (Ward & Wach, 2015, Bowen 2009)

- **Document number reviewed:** Only a limited number of documents were reviewed. A detailed assessment of a single company or a single system on all possible areas would require analysing additional documents. The number of documents analysed are directly dependent from the document amount provided by the partner company.
- **Company differences:** Each company invests a different level of time and effort in its policy documents, and the documents reviewed were different in type and style. Each document has a different level of detail, scope and focus with the intended audience and individual purpose. Any findings do not represent an overall picture of a company´s activities. A comparison between different company documents is not intended. Depending on the system analysed and its integration status, documentation may not be complete.
- **Non-universality:** Caution must be taken not to infer that the developed SCM results represent anything other than a general picture and an indicative strategic direction. For a detailed understanding of how each document was assessed and performed, it is necessary to investigate the documents themselves via the SCM. Depending on the coding approach, interpretation scheme, framework and analysis purpose, different analysts may produce deviating results.
- **Measurement:** Complexity is inherently difficult to accurately translate into a qualitative measurement. The SCM qualification scheme used are primarily indicative of trends and bigger-picture issues with goal to generate norm strategies. The coding and interpretation of a document in relation to the SCM dimensions does furthermore not represent an evaluation of its intrinsic functionality as a document of the organisation or any other functionality.

Based on these statements the next section now briefly summarizes the overall SCM case study design in the context of its decision-aiding properties.

## 12.5 Summary of SCM case study design

It is established that the SCM represents a heuristic, prescriptive-normative hybrid decision-aiding tool that allows prescriptive and normative distinct features.

These features are now put into the perspective of the chosen case study approach to discuss the applicability of the chosen case study design, as shown in Table 27.

*Table 27: Summary SCM case study design*

| **Type** | **Features** | **Case study design** |
|---|---|---|
| Prescriptive | Providing answers to a problem based on the assumptions of limited information contained in a data base by applying a heuristic approach through internal and external system complexity qualification and classification. | Data base enables internal and external system complexity qualification and classification via established document review taxonomy and interpretation scheme. |
| Normative | Deriving a priori strategic norms which intend to be universally applicable to all clients who want to behave rationally in the context of the model through the norm strategies identify, manage, and avoid. | SCM can be applied to coherently derive norm strategies based on data base analysis via QDA. |

The next chapter now introduces the conducted SCM case studies.

# 13 SCM case studies results

Building upon the achievements of the previous parts, the final part of the study now coherently answers SRQ4/ O4 and the main research question (MRQ) of this thesis.

The main motivation of this part is to contribute to the topic of strategic complexity management for industrial systems by presenting, testing, and discussing the application of the SCM.

This is achieved by testing the overall applicability of SCM on a range of real-world industrial systems within a range of market-leading European small/medium enterprises (SME) were evaluated by the author via the SCM framework in an analyst / client relationship of decision-aiding.

This chapter thus presents the results of the conducted SCM case study research, as shown in the research of Freund et al. (2021d, 2021f).

The showcased case studies have the goal to evaluate and underline the potential of application of the proposed SCM framework for practical application.

To achieve this the SCM is applied on four different, isolated cases of industrial systems obtained by two European manufacturers in Austria and Hungary.

The central goal of the conducted SCM case studies is to showcase and evaluate on a preliminary basis if the SCM is generally applicable on real-world systems.

The application of the SCM thus aims to support the overall line of argument made that SMTTs, like the SCM, can be regarded as a highly relevant holistic and practice-based approaches for decision-makers to strategically solve problems of complexity for industrial engineered systems.

The analysed cases, the SCM specific case study approach and the case study results and obtained key-learnings are described and discussed in the next sections.

## 13.1 Description SCM of case studies

This section now describes the specific research design of case study application of the SCM in correspondence to Chapter 8.

Four different industrial manufacturing systems (denoted by cases: 1, 2, 3, 4 for anonymization) located at two different international manufacturers in Hungary (H) and Austria (A) were analysed by the researcher via the SCM.

The case studies were conducted in the time between January 2021 to March 2021 and are described as showcased in the research of Freund et al. (2021d, 2021e, 2021f)

The author of this study contacted 25 European SMEs via Email in December 2020 with a concrete project proposition concerning system analysis via the SCM.

Of these 25 contacted companies, 5 companies replied with active interest in the proposed project. Two companies were selected by the author based on system scale and document availability, resulting in four different systems analysed via the SCM in four individual case studies.

The selection of cases was based on the criteria of *intensity* (information rich case, but not an extreme case), *theoretical* (case is about a theoretical construct and is used to examine and elaborate about it) and *comparability* in reference to the system to be analysed. (Campbell et.al, 2018)

Table 28 now provides further information on the context of each case.

*Table 28: SCM case descriptions*

| **Case** | **Context of case study** |
|---|---|
| 1 | Support senior management in analysis of the development and planning of an infrared lamp assembly line production system. |
| 2 | Support senior management in analysis of the development and planning of a blood pressure monitor assembly line production system. |
| 3 | Support senior management in analysis of the development and planning of a thermometer assembly line production system. |
| 4 | Support CEO in analysis of error prone automated injection moulding plant via SCM analysis. |

It can be stated that all case contexts represented concrete decision-making situations in a highly complex environment for all involved decision-makers. Table 29 now provides further information on the case sector, system status and analysed system type.

*Table 29: SCM case sector, system status and system type*

| Case | Manufacturer | Sector | System status | System type |
|---|---|---|---|---|
| 1 | H | Health & Beauty | In development | Manual assembly line |
| 2 | H | Health & Beauty | In development | Manual assembly line |
| 3 | H | Health & Beauty | In development | Manual assembly line |
| 4 | A | Silicone LSR | Active | Automated |

Table 29 shows, that three of the analysed cases (1, 2, 3) are situated in the health and beauty sector with manufacturer H and are of the same system type *manual assembly line*. The analysed assembly lines were also planned to be in the same manufacturing hall but were also planned to represent three independent systems. The status of these systems while the case studies 1,2 and 3 were conducted was therefore that these systems were still *in development*. Case 4 is situated in the Silicone LSR (Liquid-silicone rubber) sector with manufacturer A and is of the system type *automated* and with the status active during the duration of this study. Each case study now follows the same structure and tries to answer a set of corresponding questions:

- **Description:** Where and why is the SCM applied?
- **Data collection & analysis:** How can the documents be distributed among SCM levels?
- **Case results:** How can the analysed system be classified and managed in the SCM?
- **Case summary:** How can the case be summarized in the decision-aiding context?

The next section now showcases the results for each case analysed starting with Case 1.

## 13.2 Case 1: analysis of the development and planning of an infrared lamp assembly line production system

The SCM has been utilized for complexity analysis in the planning process of a new production system for infrared lamps at an international health & beauty SME.

A central motivation and goal of the SME to use SCM analysis was to support senior management in development and planning of the mentioned production line.

The SCM has been utilized for strategic complexity analysis in the analysis of the development and planning process of a partly automated infrared lamp assembly line production system.

### 13.2.1 Data collection and analysis

To achieve this, the company provided all existing documentation as the data basis for SCM analysis.

This distribution of documents is displayed in Table 30.

*Table 30: Case 1 document distribution*

| **Document Type** | **Complexity dimensions** | **Taxonomy scope** | **Taxonomy reasoning** | **Amount** |
|---|---|---|---|---|
| Production schedule | Dynamic, Environmental, Structural | Level 3 | Statement | 2 |
| Cost calculations | Dynamic, Environmental, Structural | Level 3 | Statement | 1 |
| Shop floor layouts | Structural | Level 1 | Single Sub-Systems, Product Context | 1 |
| Maintenance procedures | Dynamic | Level 2 | Method | 0 |
| Quality management | Structural, Dynamic | Level 2 | Method | 1 |
| Material treatment | Structural, Environmental | Level 2 | Method | 1 |

| | | | | |
|---|---|---|---|---|
| Operating procedures | Structural, Dynamic | Level 2 | Method | 0 |
| Supply chain | Environmental, Dynamic | Level 2 | Method | 1 |
| Other (videos etc.) | Dynamic, Environmental, Structural | Level 1-Level 3 | Misc. | 0 |

Table 30 shows, that the received 7 documents are distributed among 6 different types of documents. The shown distribution of document types on SCM dimensions is based on the specificity, purpose, and the contextual richness of the individual document in the individual dimension. (Bowen, 2009)

### 13.2.2 Case 1: results

Through the application of the SCM on the database the production system is classified as a dynamically complex system with the qualification ((S/D/E); (LOW/HIGH/LOW)). Through the application of the SCM on the database the production system is classified as a dynamically complex system with the qualification ((S/D/E); (LOW/HIGH/LOW)).

Figure 106 illustrates this.

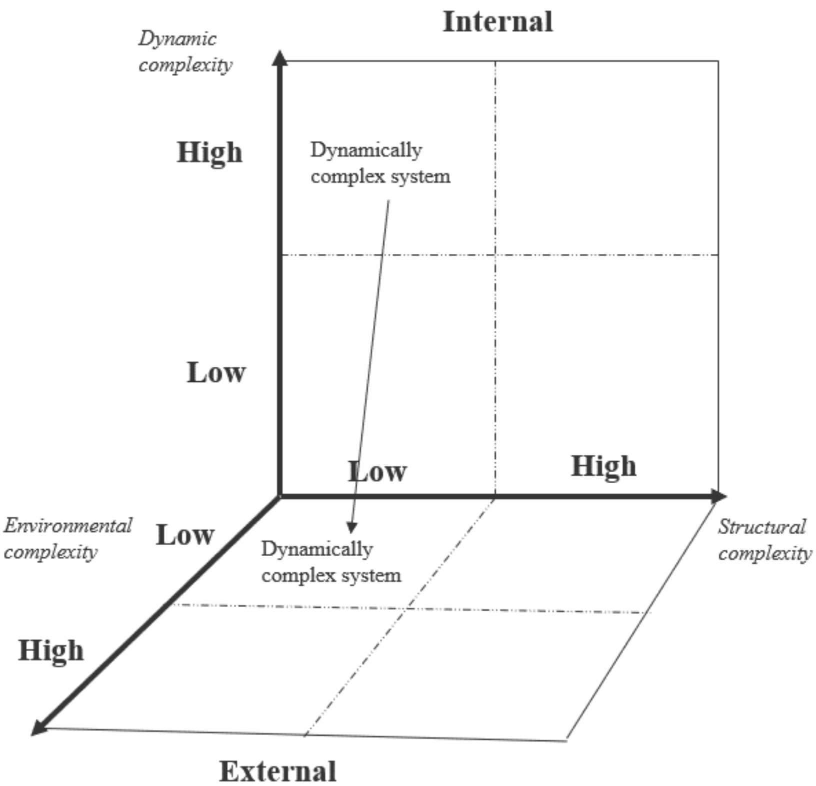



*Figure 106: SCM analysis of automated infrared assembly line*

As shown in Figure 107, the resulting norm strategy for the system is MANAGE, with intermediate system complexity and potential starting points of cost-escalation and major inefficiencies.

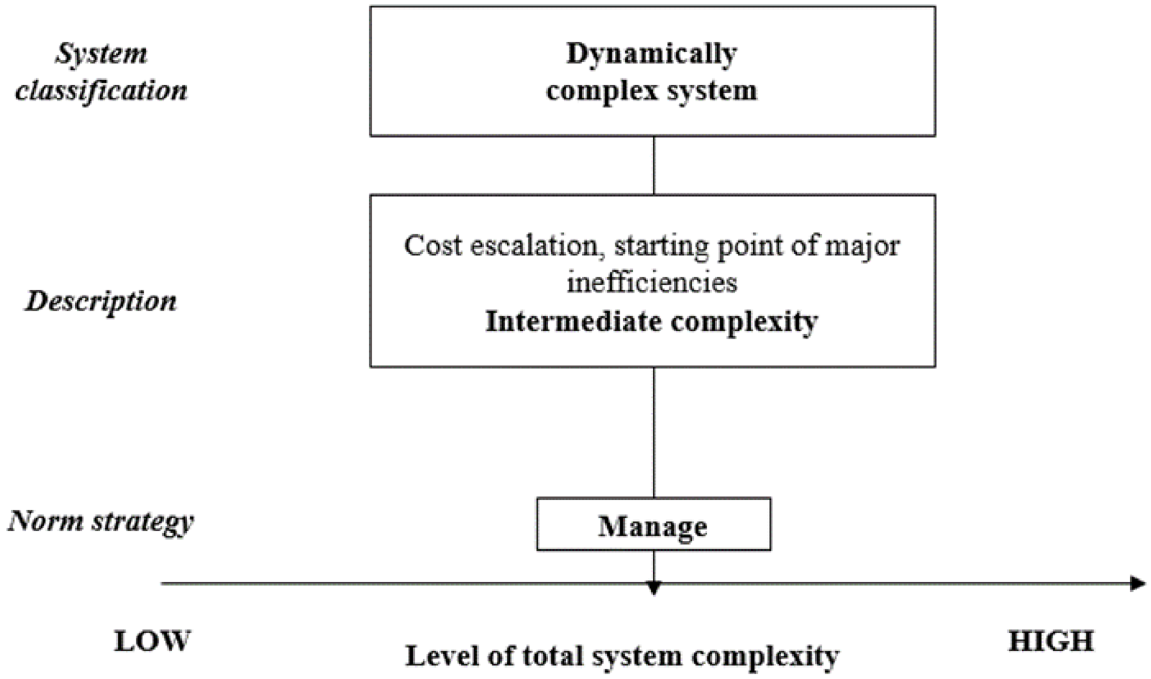



*Figure 107: Resulting norm strategy Case 1*

The following two measures were defined to allow norm strategy implementation into practice.

- Outsourcing of non-essential production steps to external suppliers
- Identification of points of cost escalation through cost scenario analysis of insourcing / outsourcing combinations of non-essential production steps

In the next section the case study is summarized.

### 13.2.3 Case 1: summary

Figure 108 summarizes Case 1 in the established decision-aiding context.

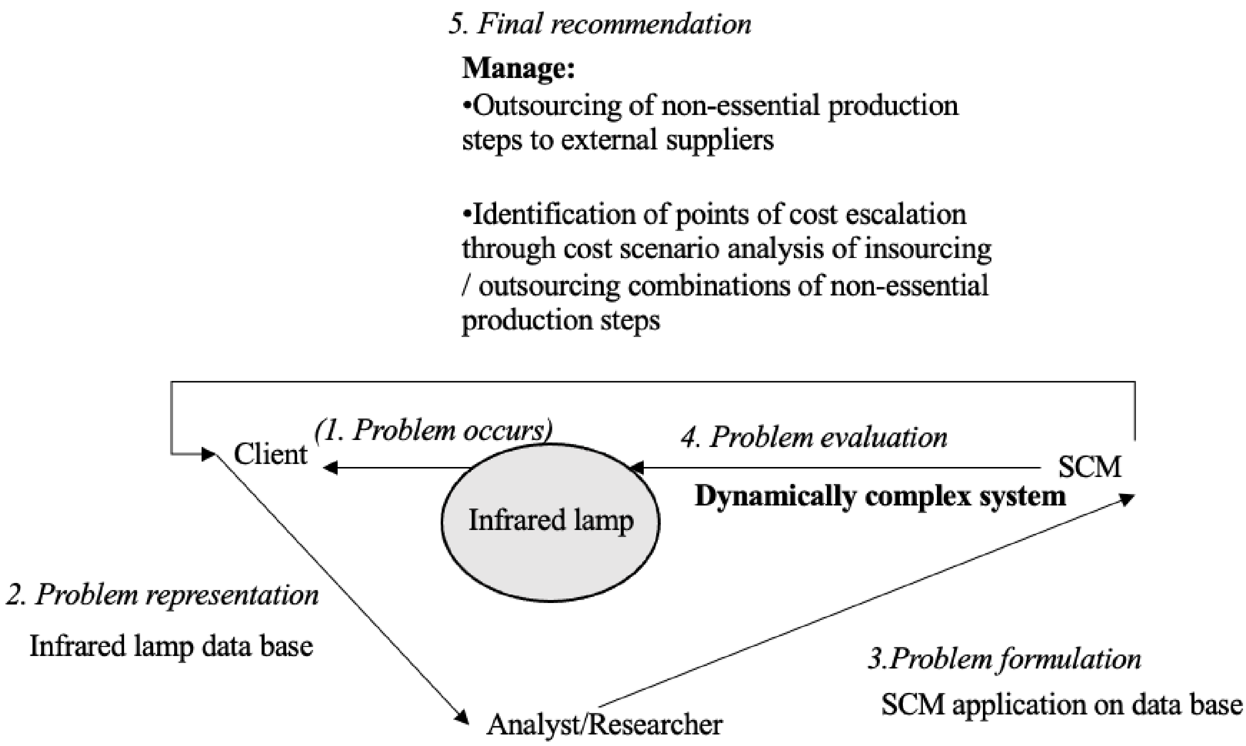



*Figure 108: Case 1 summary*

The following learnings can now be obtained for Case 1:

- Manufacturer was able to provide the research team with sufficient documents of significance and information richness to allow meaningful and valid analysis and results
- The researcher was able to apply the SCM on the case without having to depart from the framework structure and functioning or breaking the coherence of the SCM
- All received documents were successfully applied to SCM dimensions

The next section now describes Case 2.

## 13.3 Case 2: analysis of the development and planning of a blood pressure monitor assembly line production system

The SCM has been utilized for complexity analysis in the planning process of a new blood pressure monitor production system at an international health & beauty SME.

A central motivation and goal of the SME to use SCM analysis was to support senior management in development and planning of the mentioned production line.

The SCM has been utilized for complexity analysis in the development process of a partly automated blood pressure monitor assembly line.

### 13.3.1 Data collection and analysis

To achieve this, the company provided all existing documentation as the data basis for SCM analysis.

This distribution of documents is displayed in Table 31.

*Table 31: Case 2 document distribution*

| **Document Type** | **Complexity dimensions** | **Taxonomy scope** | **Taxonomy reasoning** | **Amount** |
|---|---|---|---|---|
| Production schedule | Dynamic, Environmental, Structural | Level 3 | Statement | 2 |
| Cost calculations | Dynamic, Environmental, Structural | Level 3 | Statement | 1 |
| Shop floor layouts | Structural | Level 1 | Single Sub-Systems, Product Context | 1 |
| Maintenance procedures | Dynamic | Level 2 | Method | 0 |
| Quality management | Structural, Dynamic | Level 2 | Method | 1 |
| Material treatment | Structural, Environmental | Level 2 | Method | 2 |

| | | | | |
|---|---|---|---|---|
| Operating procedures | Structural, Dynamic | Level 2 | Method | 1 |
| Supply chain | Environmental, Dynamic | Level 2 | Method | 1 |
| Other (videos etc.) | Dynamic, Environmental, Structural | Level 1-Level 3 | Misc. | 0 |

Table 4 shows, that the received 9 documents are distributed among 7 different types of documents. The shown distribution of document types on SCM dimensions is based on the specificity, purpose, and the contextual richness of the individual document in the individual dimension. (Bowen, 2009)

### 13.3.2 Case 2: results

Through the application of the SCM on the database the production system is classified as a complex system with the qualification ((S/D/E); (HIGH / HIGH / LOW))

Figure 109 illustrates this.

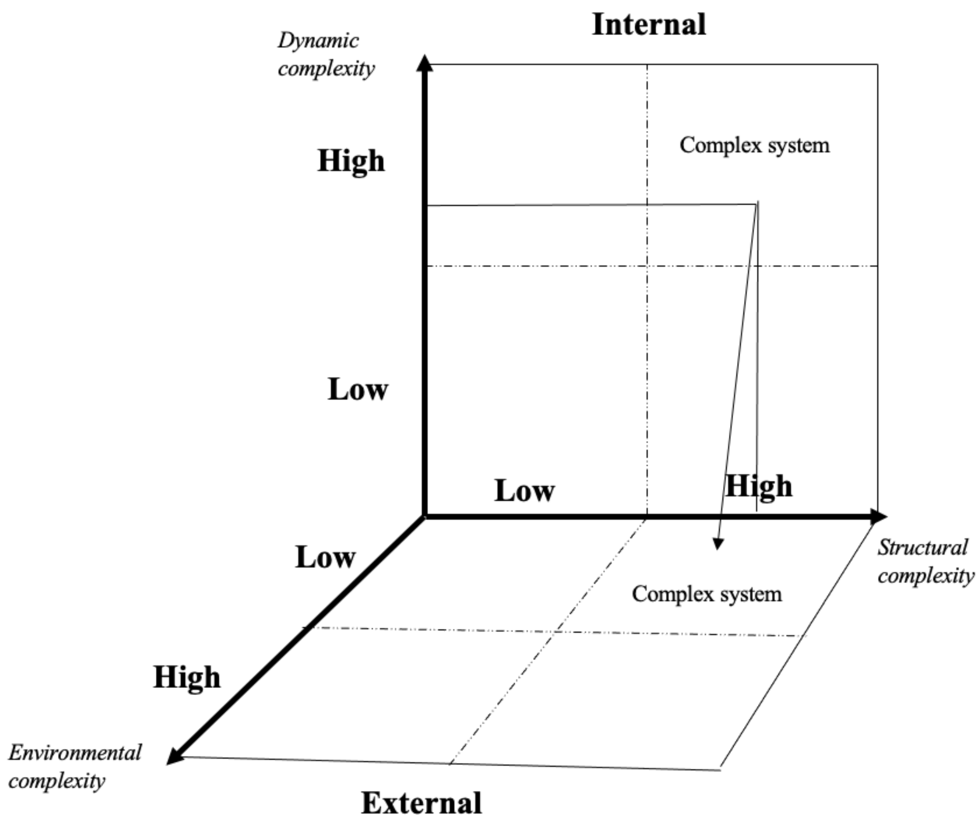



*Figure 109: SCM analysis of blood pressure monitor*

As shown in Figure 109, the resulting norm strategy for the system is AVOID, with high complexity and radical decisions necessary. This is illustrated in Figure 110.

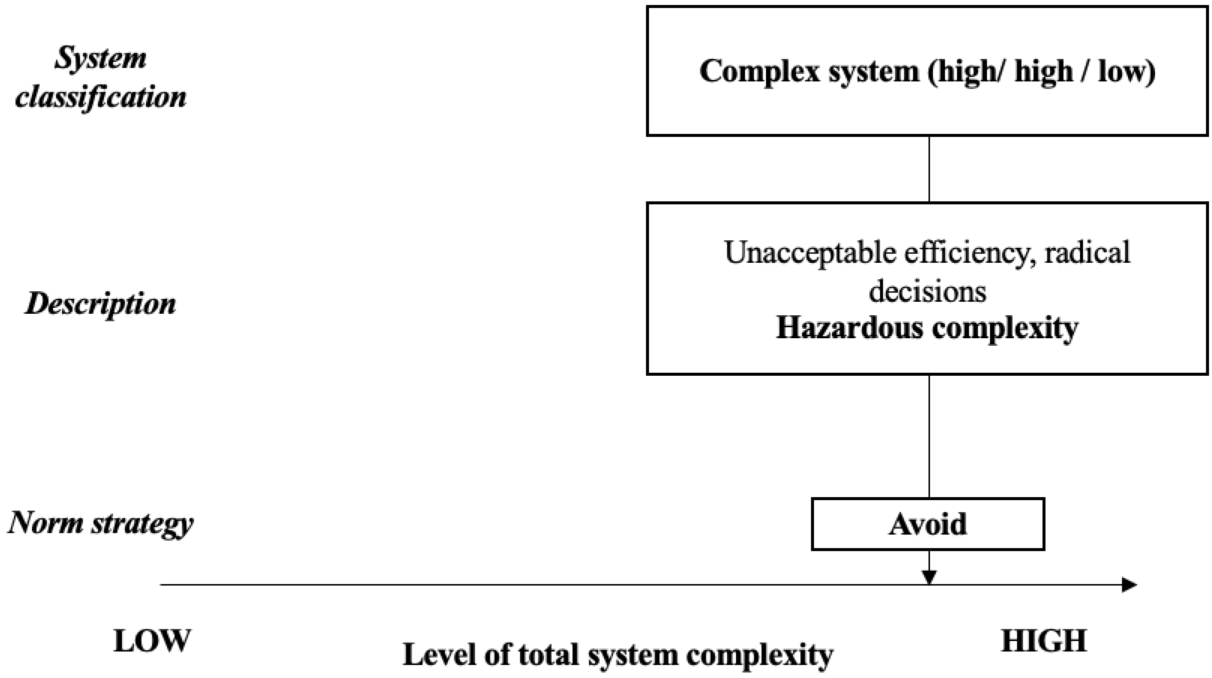



*Figure 110: Resulting norm strategy Case 2*

The following two measures were defined to allow norm strategy implementation into practice.

- Outsourcing of non-essential and essential production steps to external suppliers.
- Identification of points of cost escalation through cost scenario analysis of insourcing / outsourcing combinations of non-essential and essential production steps.

In the next section the case study is summarized.

### 13.3.3 Case 2: summary

Figure 111 summarizes Case 2 in the established decision-aiding context.

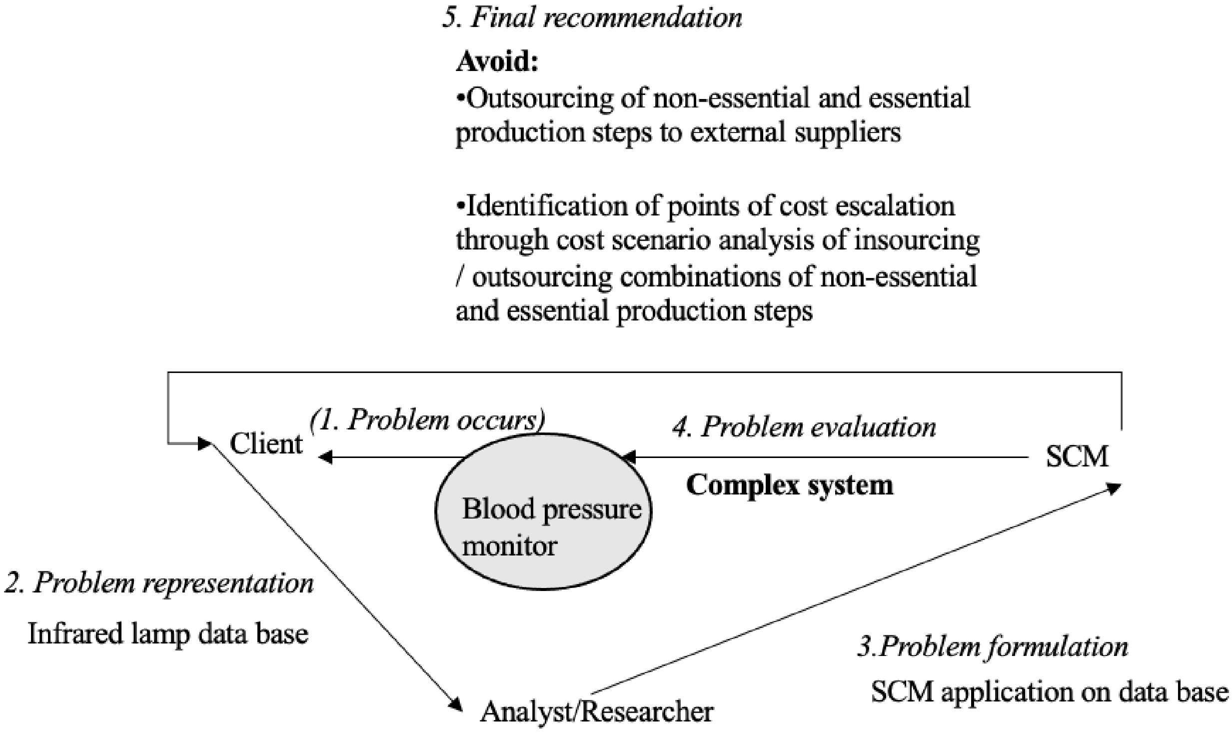



*Figure 111: Summary Case 2*

The following learnings can be obtained for Case 2:

- Manufacturer was able to provide the research team with sufficient documents of significance and information richness to allow meaningful and valid analysis and results.
- The researcher was able to apply the SCM on the case without having to depart from the framework structure and functioning or breaking the coherence of the SCM.
- All received documents were successfully applied to SCM dimensions.
- The SCM was capable to generate valid results in the form of norm strategies for all analysed cases.

The next section now describes Case 3.

## 13.4 Case 3: analysis of the development and planning of a thermometer assembly line production system

The SCM has been utilized for complexity analysis in the planning process of a new production system at an international health & beauty SME.

A central motivation and goal of the SME to use SCM analysis was to support senior management in development and planning of the mentioned production line.

The SCM has been utilized for complexity analysis in the analysis of the development and planning of a thermometer assembly line production system.

### 13.4.1 Data collection and analysis

To achieve this, the company provided all existing documentation as the data basis for SCM analysis.

This distribution of documents is displayed in Table 32.

*Table 32: Case 3 document distribution*

| **Document Type** | **Complexity dimensions** | **Taxonomy scope** | **Taxonomy reasoning** | **Amount** |
|---|---|---|---|---|
| Production schedule | Dynamic, Environmental, Structural | Level 3 | Statement | 1 |
| Cost calculations | Dynamic, Environmental, Structural | Level 3 | Statement | 1 |
| Shop floor layouts | Structural | Level 1 | Single Sub-Systems, Product Context | 2 |
| Maintenance procedures | Dynamic | Level 2 | Method | 0 |
| Quality management | Structural, Dynamic | Level 2 | Method | 1 |
| Material treatment | Structural, Environmental | Level 2 | Method | 1 |

| | | | | |
|---|---|---|---|---|
| Operating procedures | Structural, Dynamic | Level 2 | Method | 3 |
| Supply chain | Environmental, Dynamic | Level 2 | Method | 1 |
| Other (videos etc.) | Dynamic, Environmental, Structural | Level 1-Level 3 | Misc. | 1 |

Table 32 shows, that the received 11 documents are distributed among 8 different types of documents. The shown distribution of document types on SCM dimensions is based on the specificity, purpose, and the contextual richness of the individual document in the individual dimension. (Bowen, 2009)

### 13.4.2 Case 3: results

Through the application of the SCM on the database the production system is classified as a complex system with the qualification ((S/D/E); (HIGH / HIGH / LOW))

Figure 112 illustrates this.

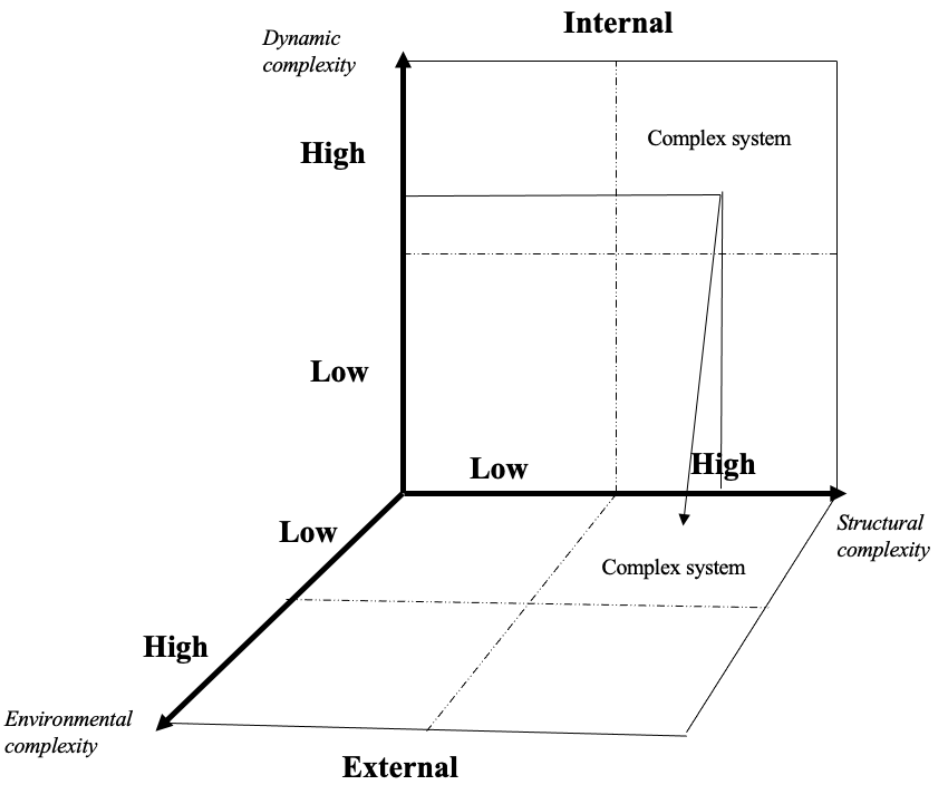



*Figure 112: SCM analysis of thermometer assembly line*

As shown in Figure 113, the resulting norm strategy for the system is AVOID, with high complexity and radical decisions necessary. This is now displayed in Figure 117.

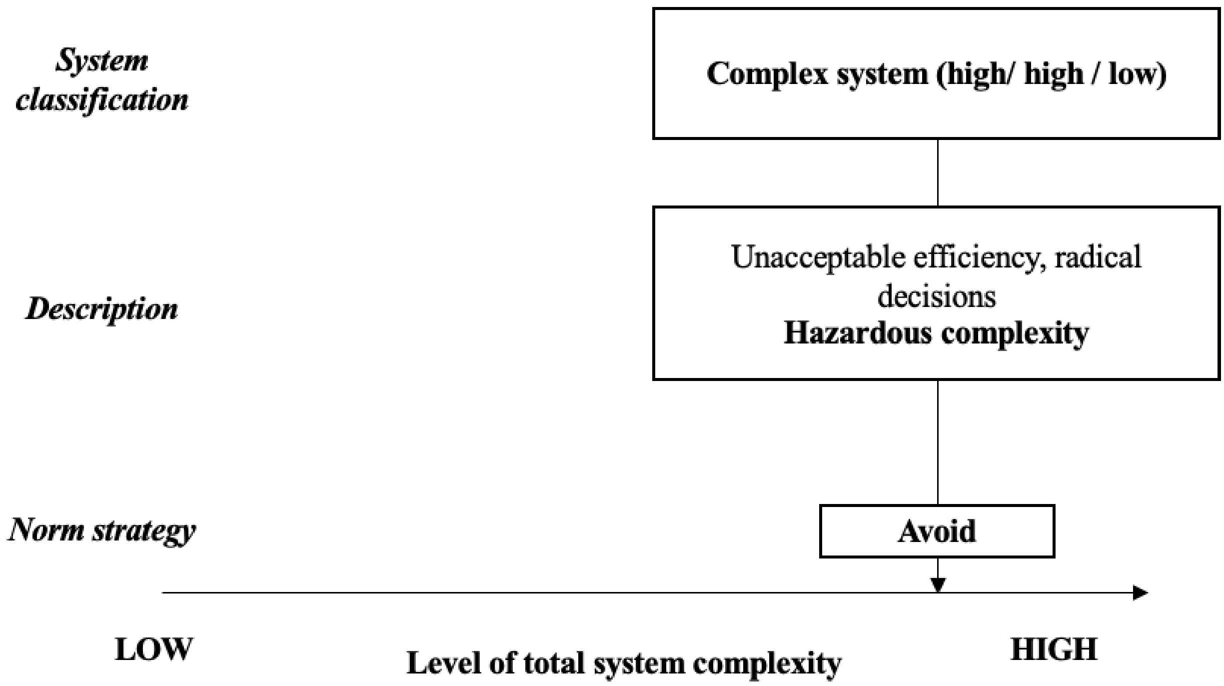



*Figure 113: Resulting norm strategy Case 3*

The following two measures were defined to allow norm strategy implementation into practice.

- Outsourcing of non-essential and essential production steps to external suppliers.
- Identification of points of cost escalation through cost scenario analysis of insourcing / outsourcing combinations of non-essential and essential production steps

In the next section the case study is summarized.

### 13.4.3 Case 3: summary

Figure 114 summarizes Case 3 in the established decision-aiding context.

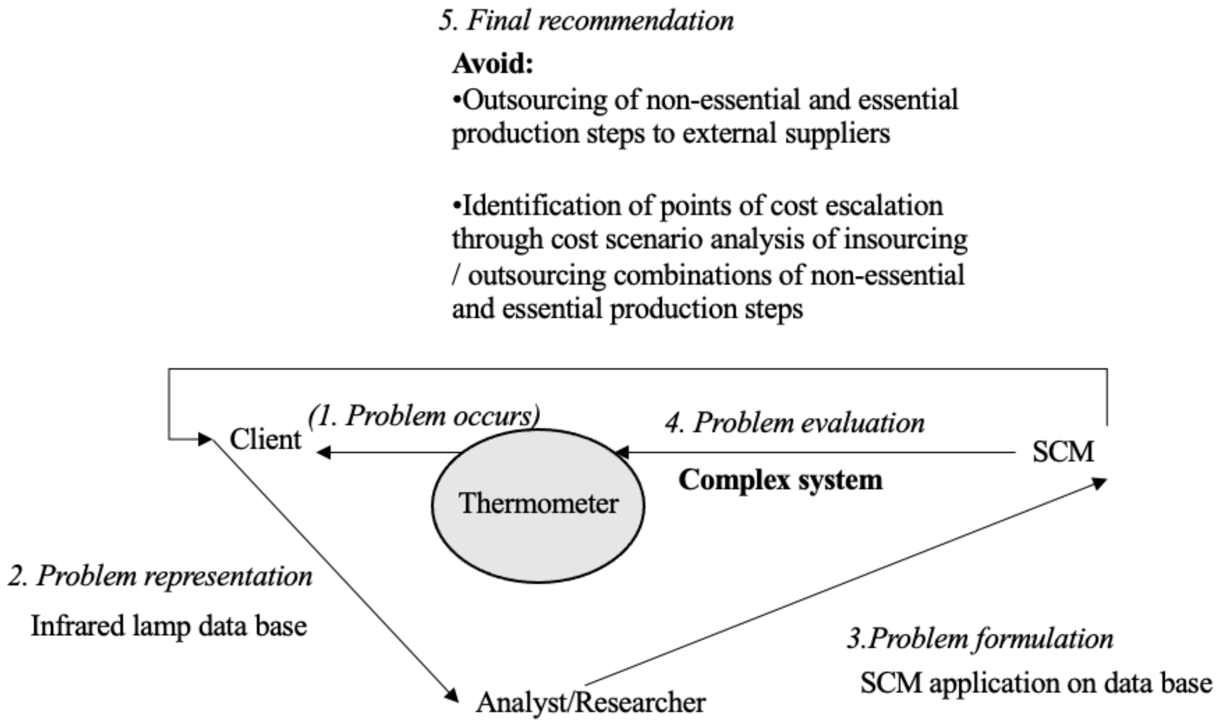



*Figure 114: Summary Case 3*

The following learnings can be obtained:

- Manufacturer was able to provide the research team with sufficient documents of significance and information richness to allow meaningful and valid analysis and results.
- The researcher was able to apply the SCM on the case without having to depart from the frame-work structure and functioning or breaking the coherence of the SCM.
- All received documents were successfully applied to SCM dimensions.
- The SCM was capable to generate valid results in the form of norm strategies for all analysed cases.

The next section now describes Case 4.

## 13.5 Case 4: automated injection molding plant

The SCM has been utilized for complexity analysis in the analysis of the maintenance process of an automated injection moulding system at a European LSR manufacturer which had an increased rate of unexpected, abnormal errors.

A central motivation and goal of the SME to use SCM analysis was to support senior management in reducing system downtime and unexpected error rate of the mentioned production line.

The SCM has been utilized for complexity analysis in the analysis of the maintenance process of an automated injection moulding system at an European LSR manufacturer which had an increased rate of unexpected, abnormal errors.

### 13.5.1 Data collection and analysis

To achieve this, the company provided all existing documentation as the data basis for SCM analysis. The Case 4 data base is shown in Table 33.

*Table 33: Case 4 document distribution*

| **Document Type** | **Complexity dimensions** | **Taxonomy scope** | **Taxonomy reasoning** | **Amount** |
|---|---|---|---|---|
| Production schedule | Dynamic, Environmental, Structural | Level 3 | Statement | 3 |
| Cost calculations | Dynamic, Environmental, Structural | Level 3 | Statement | 3 |
| Shop floor layouts | Structural | Level 1 | Single Sub-Systems, Product Context | 1 |
| Maintenance procedures | Dynamic | Level 2 | Method | 2 |
| Quality management | Structural, Dynamic | Level 2 | Method | 2 |
| Material treatment | Structural, Environmental | Level 2 | Method | 3 |

| | | | | |
|---|---|---|---|---|
| Operating procedures | Structural, Dynamic | Level 2 | Method | 2 |
| Supply chain | Environmental, Dynamic | Level 2 | Method | 3 |
| Other (videos etc.) | Dynamic, Environmental, Structural | Level 1-Level 3 | Misc. | 0 |

Table 33 shows, that the received 33 documents are distributed among 6 different types of documents. The shown distribution of document types on SCM dimensions is based on the specificity, purpose, and the contextual richness of the individual document in the individual dimension. (Bowen, 2009)

### 13.5.2 Case 4: results

Through the application of the SCM on the database the production system is classified as a dynamically complex system with the qualification ((S/D/E); (LOW/HIGH/LOW)).

Figure 115 illustrates this.

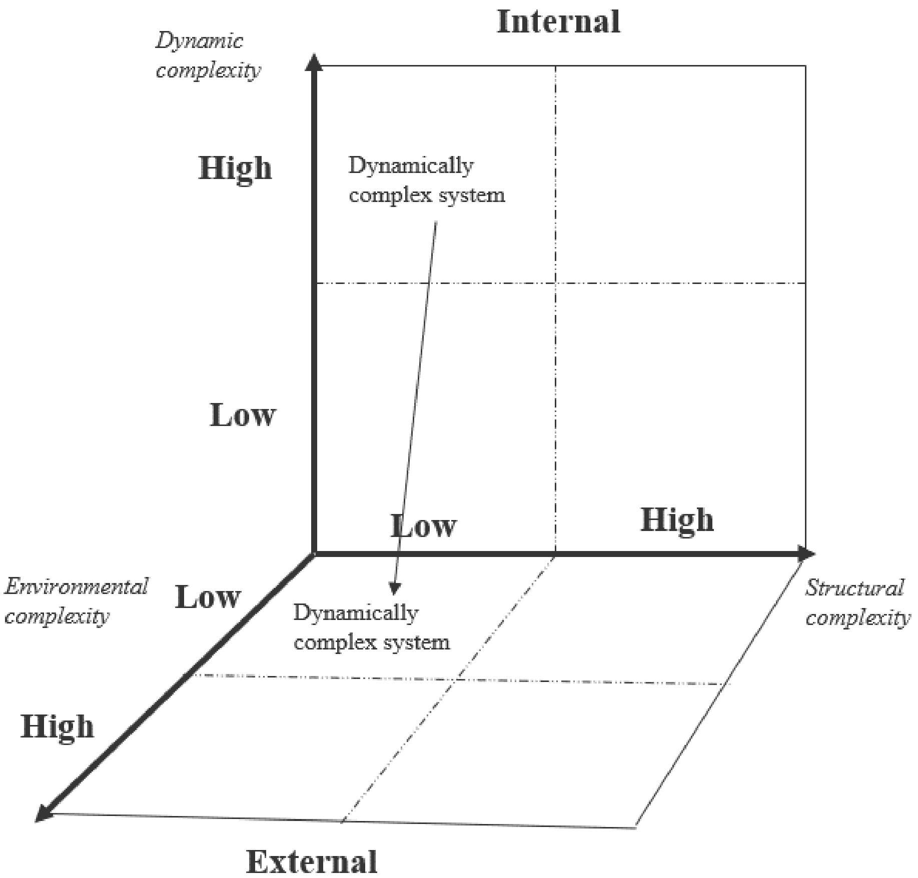



*Figure 115: SCM analysis of automated injection molding plant*

As shown in Figure 116, the resulting norm strategy for the system is MANAGE, with intermediate system complexity and potential starting points of cost-escalation and major inefficiencies.

This is now illustrated in Figure 116.

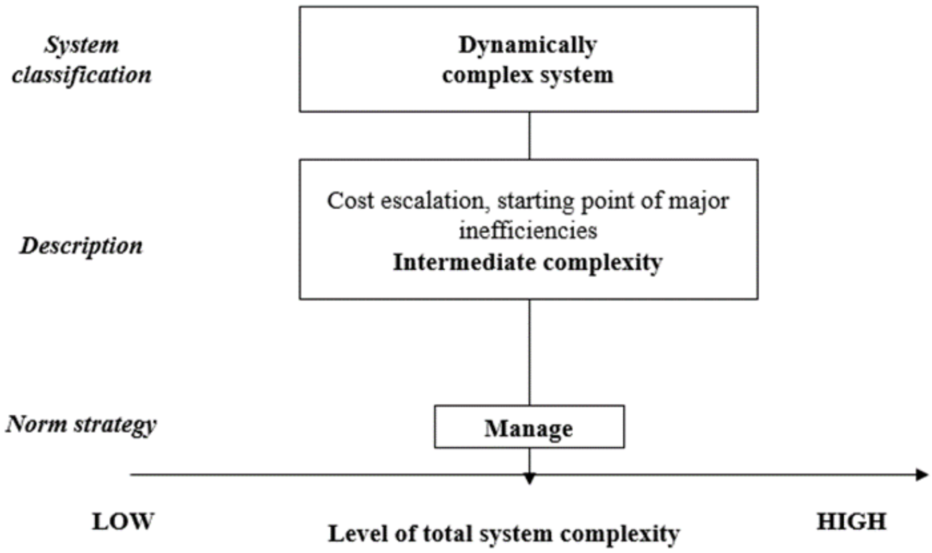



*Figure 116: Resulting norm strategy Case 4*

The following measures were determined based on the SCM analysis.

- Anticipating: Intensified Due-Diligence program based on 5S and Kaizen approach with the goals: understanding the complexity of the system, building practical knowledge of the system, invention of new approach for maintenance.

- Reactive: Introduction of an expert group of consisting of interdisciplinary specialists that can react when an unexpected error occurs. This group has furthermore the goal to track, archive and report.

In the next section the case study is summarized.

### 13.5.3 Case 4: summary

Figure 117 summarizes Case 4 in the established decision-aiding context.

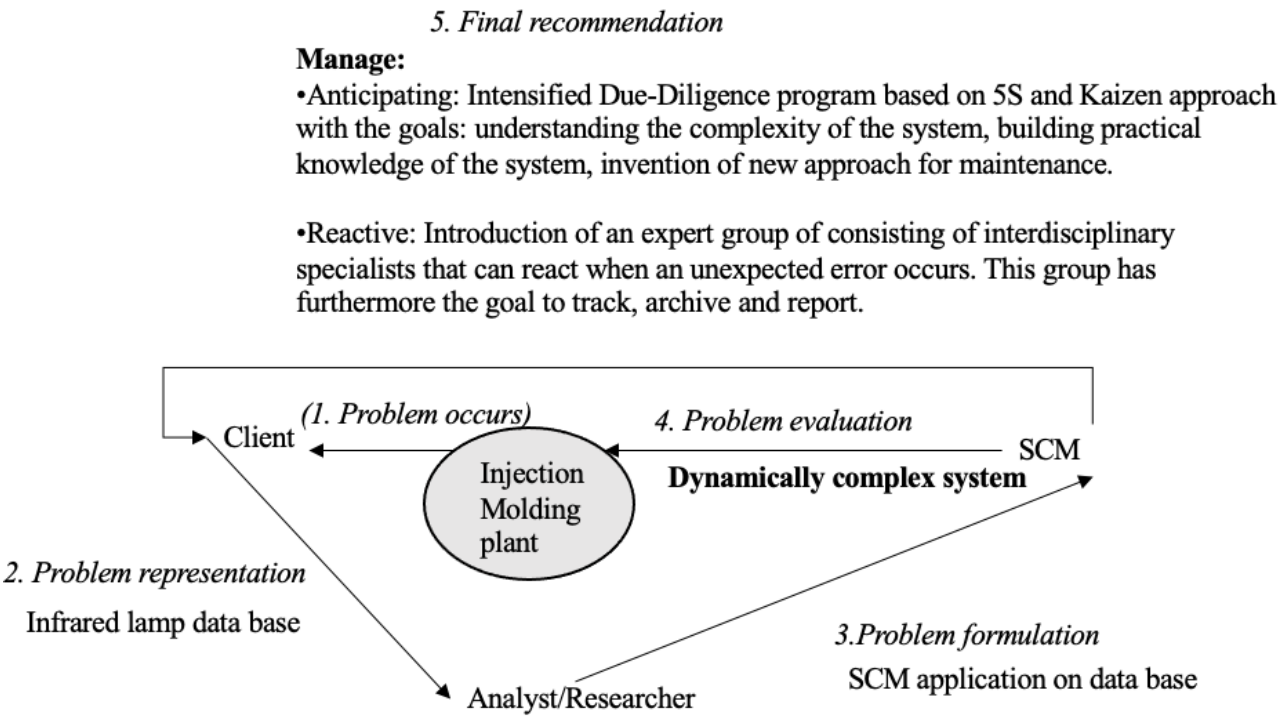



*Figure 117: Summary Case 4*

The following learnings can be obtained:

- Manufacturer was able to provide the research team with sufficient documents of significance and information richness to allow meaningful and valid analysis and results.
- The researcher was able to apply the SCM on the case without having to depart from the framework structure and functioning or breaking the coherence of the SCM.
- All received documents were successfully applied to SCM dimensions.
- The SCM was capable to generate valid results in the form of norm strategies for all analysed cases.
- The generated SCM norm strategies were successfully implemented into practice.

After presenting all cases in detail, the next section provides an overview of the results.

## 13.6 Overview of case study results

Table 34 now shows the isolated SCM classification and qualification for each case analysed.

*Table 34: Case studies classifications and qualifications*

| Case | Classification | Qualification (S/D/E) |
|---|---|---|
| 1 | Dynamically complex | Low / High / Low |
| 2 | Complex | High / High / Low |
| 3 | Complex | High / High / Low |
| 4 | Dynamically complex | Low / High / Low |

Table 35 now illustrates the resulting norm strategy distribution for each case.

*Table 35: Case studies norm strategies*

| Case | Norm strategy |
|---|---|
| 1 | *Manage:* Identification of cost escalation |
| 2,3 | *Avoid:* Radical decisions |
| 4 | *Manage:* Identification of cost escalation |

Table 35 shows that it was possible to derive a norm strategy for each analysed case via the SCM that is coherent with the framework.

To achieve practical implementation the SCM norm strategies were then applied as strategic guidance and direction to achieve a more specific context-oriented strategies for the individual manufacturer.

The resulting context-oriented strategies are now described and represent the practical interpretation and implementation of the generated SCM norm strategies displayed in Table 36.

Table 36 now describes the context-oriented strategies for each analyzed case.

*Table 36: Case studies context-oriented strategies*

| **Case** | **Context-oriented strategy** |
|---|---|
| 1 | *Manage:* Outsourcing of non-essential production steps to external suppliers; Identification of points of cost escalation through cost scenario analysis of insourcing / outsourcing combinations of non-essential production steps. |
| 2, 3 | *Avoid:* Outsourcing of non-essential and essential production steps to external suppliers; Identification of points of cost escalation and steps that can potentially be outsourced through cost scenario analysis of insourcing / outsourcing combinations of production of essential and non-essential production steps. |
| 4 | *Manage:* Cost management and identification of points of cost escalation through definition and implementation of combination of reactive (Kaizen approach) and anticipative (establishment of expert group as main investigators in the case of unknown errors) measures. |

Table 36 shows, that it was possible to derive specific context-oriented strategies based on the SCM norm strategies that are meaningful, applicable, and helpful for the individual context of the analysed cases.

The next section now provides a brief cross-case analysis of the results obtained in the individual case to derive key-learnings out of the cases conducted via the SCM.

### 13.6.1 Key-learnings

Based on the cross-case comparison and the results of the SCM analysis for the cases 1, 2, 3, 4 the following six key-learnings were obtained after the case study SCM analysis.

It is important to state at this point that the key-learnings obtained primarily refer to the overall applicability of the framework and not to the applicative value of the strategies derived, especially not in a long-term perspective.

The obtained key-learnings of the collective body of cases are now displayed in Table 37.

*Table 37: Case studies cross-case analysis*

| **Key-learning** | **Description** |
|---|---|
| Documentation | Manufacturers were able to provide the research team with sufficient documents of significance and information richness to allow meaningful and valid analysis and results. |
| Framework applicability | The research team was able to apply the SCM on a range of divergent cases without having to depart from the framework structure and functioning or breaking the coherence of the SCM. |
| Document integration | All received documents were successfully integrated into the chosen document typology. |
| Document interpretation | All received documents were successfully applied to SCM dimensions. |
| SCM norm strategies | The SCM was capable to generate valid results in the form of norm strategies for all analysed cases. |
| Norm strategy applicability | The generated SCM norm strategies were successfully applied for the generation of context-oriented strategies without exception. |

The next section now provides a discussion of the obtained case study results.

## 13.7 Limitations & discussion of case study results

As shown and described, four isolated case studies were conducted via SCM based on four individual complexity management problems.

The application and results generated by the SCM, and the key-learnings obtained indicate that holistic practice-based SMTTs for strategic complexity management can provide meaningful and helpful assistance to decision-makers in the manufacturing industry in the process of strategy development when dealing with complex problems concerning volatility, uncertainty, complexity, and ambiguity.

Due to the system types of cases analysed, even though still complex, it remains unclear if SMTTs are also as useful in the context of hyper-complex, less traditional and generally less understood systems like CPS and CPSS. It is also unclear how valuable the SCM analyses are in a mid to long term perspective. Also, CPS systems might be documented in more unorthodox or non-standard ways and document analysis might be less efficient and effective for the SCM.

Results are also inherently limited by QDA limitations and contain a subjective, interpretive component induced by the researcher in the role of the analyst, documents received, company bias and many more, and are thus not to be regarded as objective or universal. Consequently, the obtained results shall be regarded as indicative of the general applicability of the SCM. Nevertheless, the results show that the SCM is capable to generate results and a strategic directive for each case, while always adhering to the framework structure and format.

The obtained case study results allow to draw the following central implication for the applicative value of the approach which is illustrated by Figure 118.

Figure 118 now shows the position of the SCM in the strategic complexity management cycle.

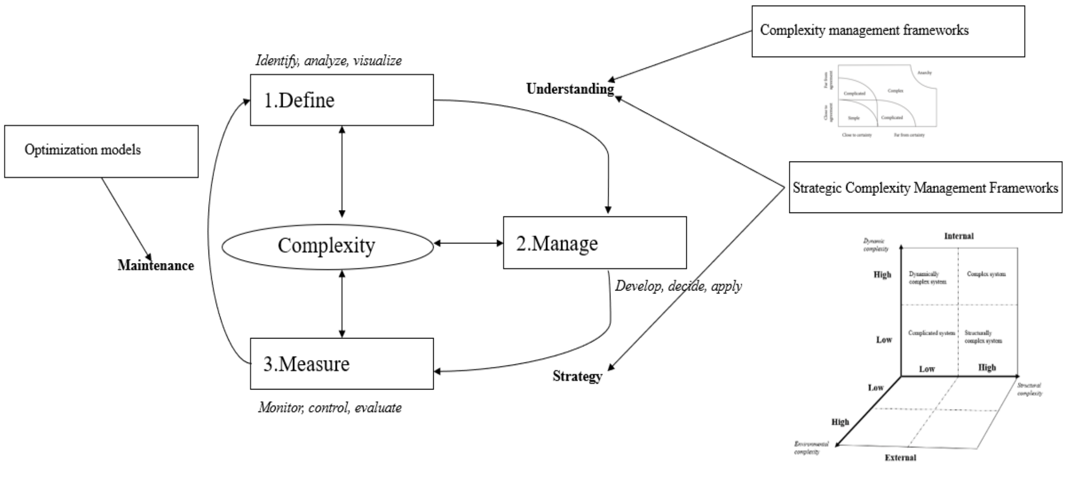



*Figure 118: The SCM in the context of the strategy gap of complexity management frameworks*

Figure 118 shows that the SCM is expected to be applied to the steps Define and Manage in the cycle and provides an answer to the identified strategy gaps of complexity management frameworks.

The application and results generated by the individual SCM case studies, and the key-learnings obtained allow to indicate that holistic practice-based SMTTs for strategic complexity management, like the SCM, can provide meaningful and helpful assistance to decision-makers in the manufacturing industry in the process of strategy development when dealing with complexity problems in industrial systems.

Finally, it can be concluded that the SCM is expected to be applied to the steps understanding and strategy in the strategic complexity management cycle and provides a first answer to the identified strategy gap of complexity management frameworks.

SRQ4 can now be answered.

- ***Sub-research question 4 (SRQ4; O4):*** **Can a strategic complexity management framework be applied on real-world industrial systems?**

  ***Answer****:* Based on the results obtained in the conducted case studies, it can be established that the SCM can be generally applied on real world industrial systems and can solve the identified strategy gap in complexity management frameworks.

After answering SRQ4 and achieving the corresponding objective O4, the MRQ of this thesis can now be answered.

- ***Main research question (MRQ):*** **Can the complexity of industrial manufacturing systems be managed via a strategic complexity management framework?**

  ***Answer:*** Based on the results of the conducted case study research, the complexity of an industrial manufacturing system can be generally managed via the SCM.

After answering the MRQ and achieving O4, the final chapter of this study now presents the conclusion to this thesis.

# 14 Conclusion & outlook

This study shows through the developed hypotheses H1-H3 that it can be theoretically indicated that the amount information aggregated and transferred in a system can serve as an indicator for the development of system complexity and as a possible explanatory concept for the surges of system complexity in industrial information systems, like CPS.

It is shown via H1-H13 that the act of system regulation is highly dependent on the underlying complexity und disturbance set of the system. A growth of system complexity thus leads for the rational decision maker to a proportional increase in choice risk and choice uncertainty, leading to up to an increasingly difficult decision-making process.

This is described through the “complex system performance / risk trade-off”. The thesis furthermore provides a first approach to consistently model the relationship of disturbance, regulatory response, outcome, and outcome desirability via the described matrixes. Additionally, an argument for heuristics in complex systems management via SMTTs is made and a strategy gap in existing complexity management frameworks is identified.

A complexity space modelling approach for industrial system complexity is introduced and aims to serve as a conceptual modelling approach with the primary function of early-stage exploratory system analysis and enabling more advanced modelling and simulation approaches, as well as the construction of dedicated strategic complexity management SMTTs.

The model is based on the axiomatic conception of a three-dimensional static complexity space in which informational complexity is modelled as a sphere that expands dynamically over time until expansion is limited by the boundaries of complexity space.

It can be concluded in the context of the model, that any industrial system maximizes information complexity over time and thus also maximizes entropy over time, making the system increasingly prone to error, hazardous and cost intensive over time, if the system information complexity expansion is not adequately artificially controlled via an external control system of proportionate size and ability.

A strategic complexity framework in the form of the SCM is introduced and functions as a practice based SMTT for complexity analysis of current and future complex industrial systems. The dimensions of the model in the form of structural, dynamic, and environmental complexity are introduced and described.

The core capabilities in the form of system qualification, classification, and norm strategies of the SCM framework are theoretically demonstrated.

The SCM is applied on four different cases obtained by two European manufacturers in Austria and Hungary.

The application and results generated by the SCM case studies, and the key-learnings obtained indicate that holistic practice-based SMTTs for strategic complexity management, like the SCM, can provide meaningful and helpful assistance to decision-makers in the manufacturing industry in the process of strategy development when dealing with complex problems in industrial system management.

*There are now many open directions for future work:*

Conducting more similar, real-world case study applications and cross-case analysis would be helpful to define the practical value of the norm strategies of the SCM more clearly.

Applying the SCM on real-word CPS and it would be interesting to study current real-world complex industrial systems through complexity space modelling in more detail, perhaps even in a combined approach.

Longitudinal case applications of the SCM framework would help in understanding the long-term value of results.

Also, it appears necessary to further explore the validity of the hypotheses H1-H13 proposed by conducting further research for example through more specified literature review, system simulations or dedicated case study research, especially in the area of the notion of complexity and the practical applications of complex industrial information systems in the form of CPS.

In the context of the developed complexity space model, it would be interesting to further analyse the behaviour of information growth in current and future industrial systems. It would be interesting to study current real-world systems, like cyber-physical systems, through complexity space modelling in more detail and explore potential simulation capabilities of the model.

Finally, it appears reasonable to propose further investigations on how the SCM is used by managers in practice and how it supports management activities in a company environment.

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# APPENDIX

| Related publications |
|---|
| • Lucas Freund, Salah Al-Majeed, “Managing Industry 4.0 Integration”, Logforum 17.4 (2021)<br>• Freund, Lucas, and Salah Al-Majeed. "Hypotheses concerning complexity surges in modern and future industrial information systems ." Logforum 17.3 (2021): 1. DOI: 10.17270/J.LOG.2021.3.1<br>• L. Freund and S. Al-Majeed, "Modelling Industrial IoT System Complexity," 2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT), 2020, pp. 1-5, doi: 10.1109/3ICT51146.2020.9311942.<br>• L.Freund, S. Al-Majeed & A. Millard, “Complexity Space Modelling for Industrial Manufacturing Systems”, International Journal of Computing and Digital Systems, ISSN (2210-142X)<br>• L. Freund and S. Al-Majeed, "Cyber-Physical Systems as Sources of Dynamic Complexity in Cyber-Physical-Systems of Systems," 2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT), 2020, pp. 1-5, doi: 10.1109/3ICT51146.2020.9312015.<br>• L. Freund, S. Al-Majeed and A. Millard, "Towards the Definition of a Strategic Complexity Management Framework for Complex Industrial Systems," 2021 16th International Conference of System of Systems Engineering (SoSE), 2021, pp. 210-215, doi: 10.1109/SOSE52739.2021.9497491.<br>• L. Freund, S. Al-Majeed and A. Millard, "Case Studies Key-Findings of a Strategic Complexity Management Framework for Industrial Manufacturing Systems," 2021 16th International Conference of System of Systems Engineering (SoSE), 2021, pp. 55-60, doi: 10.1109/SOSE52739.2021.9497489<br>• Lucas Freud, Salah Al-Majeed and Alan Millard, Case study application of a strategic complexity management framework for complex industrial systems, INTERNATIONAL SCIENTIFIC JOURNAL "INDUSTRY 4.0" WEB ISSN 2534-997X; PRINT ISSN 2534-8582<br>• Lucas Freund, Salah Al-Majeed. (2020). The Industry 4.0 Knowledge & Technology Framework. PalArch’s Journal of Archaeology of Egypt / Egyptology, 17(9), 6321 - 6339. |

# Declaration

This dissertation is the result of my own work and includes nothing, which is the outcome of work done in collaboration except where specifically indicated in the text.

It has not been previously submitted, in part or whole, to any university of institution for any degree, diploma, or other qualification.

**Signed:**

**Date:** 20.05.2022