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Weighted Particle Swarm Optimization Algorithms and Power Management Strategies for Grid Hybrid Energy Systems †

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Abstract: In independent renewable energy systems (RESs), one of the primary concerns needing to be addressed is the maintaining of power balances between supplies and requirements that are cost-optimized in residences linked to these systems. The amount of power generated through RESs has substantially risen, with solar and wind being the two primary sources in RESs. In modern power systems, small-scale distributed networks are growing at a rapid pace and distributed generation (DG) plays an important role. Micro grids are very recent additions to electrical infrastructures. Power management is primarily required for smooth operation, maintaining consistency, and robustness, as well as controlling the actual and reactive power of independent DG. However, the batteries are expensive; moreover, during the charging and discharging process, huge amounts of power are lost, characterizing important problems which have to be averted. This paper introduces the weighted particle swarm optimization (WPSO) method for controlling energy systems and grid hybrid energy systems that comprise photovoltaic (PV), wind turbine, batteries, and diesel generators. By maximizing the power derived from RES and reducing battery power usage, energy is preserved, and the cost of energy consumption (energy of diesel) is reduced. Meteorological data from Spain were used in this study's simulations. The method depends on the data forecast of renewable energy one day in advance and the everyday load power consumption profile. The results of the simulation show that WPSO outperforms existing algorithms in terms of energies, costs, and battery lives.

Keywords: weighted particle swarm optimization (WPSO); energy management system; grid hybrid energy system; PV (photovoltaic); DG (distributed generation); renewable energy systems (RESs)

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1. Introduction

The progress achieved in the electrical business, including deregulation and DG to find a solution to the energy and environmental challenges, has significantly improved. The concept of micro grids has gained prominence as DG and power electronic technology have advanced quickly [1,2]. Due to structural and functional changes, the various settings in a micro grid will be AC, DC, or combinations of AC/DC. Micro grids can be defined as localized collections of electrical sources where they operate in connected or island modes. In connected modes, these grids operate independently of utility grids and are connected to utility grids to consume/supply electricity from/to power systems [3].

Attention is increasing towards the fusion of RESs to power systems because the incorporation of micro grids can improve robustness and scalability [4–6]. One disadvantage of hybrid micro grids is that they does not have the power to deal with different kinds of loads to be rated AC frequencies for AC grids and rated DC voltages for DC grids. Hybrid micro grids are produced through fusion; however, they exhibit operational issues. A unique approach is presented in this paper, considering various rated AC frequencies and DC.

Figure 1 depicts the structure of micro grids and EMS, using bidirectional AC/DC converters (BADCs) to connect to power grids and bidirectional DC/DC converters (BDDCs), made up of AC and DC buses with solar cells and wind turbines as generation sources. The micro grid's autonomous operational modes have many issues, including voltage sags, harmonics, and voltage flickers, which have been highlighted elsewhere [7,8].

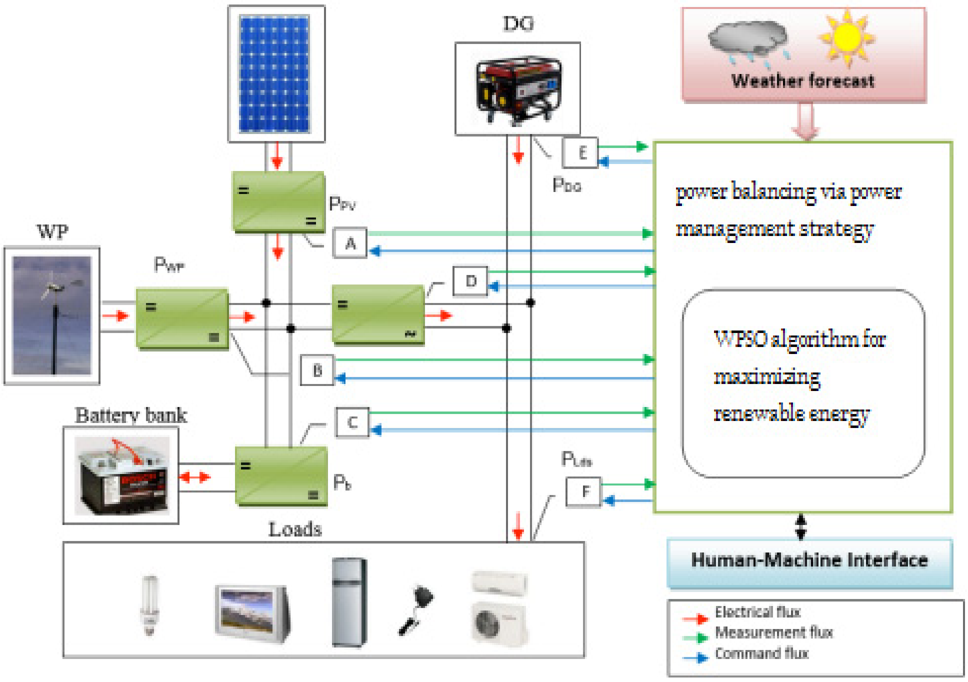

Figure 1. Overall framework for the proposed WPSO algorithm for HES.

For stable loads, hybrid solar/wind and battery systems are used. Peak demand increases the possibility of energy supply shortages, boosting energy storage device ratings. The excess power in these systems is dissipated by applying constant dump loads. When systems display prolonged periods of surplus energy, it is difficult to disperse them with constant dump loads. This paper describes hybrid systems of solar/wind/battery energies with deferrable primary and dump loads [9].

Hybrid micro grids need a method for proper power regulation in order to operate effectively and seamlessly [10].

The primary objectives of this technical study involved energy management systems and grid hybrid energy systems. Many studies and techniques have been presented; however, better energy savings and costs are not often attained. To resolve these issues, in this study, the WPSO algorithm is introduced for improving overall system performance. The primary contribution made by this study is system modelling, storage system power, and power balancing using power management strategies and the WPSO algorithm for the utilization of renewable energy. The proposed technique is helpful for achieving results with better accuracy using efficient algorithms for the provided setup.

The rest of this study is structured as follows: Section 2 provides a literature review of power management strategy and renewable energy studies; Section 3 provides the proposed power management mechanism comprehensively; Section 4 introduces the outcomes achieved with the experiments; Section 5 provides the conclusion of the paper.

2. Related Work

Cao et al. (2011) presented unique battery/ultra capacitor hybrid energy storage systems (HESSs) for electrically driven automobiles, such as electric, hybrid electric, and plug-in hybrid electric vehicles [11].

Bocklisch et al. (2015) discussed common HESS applications, energy storage coupling frameworks, fundamental concepts in power management, and significant methods for splitting currents based on double low-pass filtering and peak cancellation [12]. Their results were supported by a brief overview of the experimental HESS testing platform developed at Chemnitz University of Technology.

HESs based on solar/wind energies were addressed by Sanajaoba et al. (2019) [13]. Their system attracted global attention for remote applications, specifically in places where grid supplies could not be extended. When LOLP values were greater than 0.03, the system became unworkable since COEs rose.

Barelli et al. (2020) presented a revolutionary HESS power management system that combines flywheels and $LiFePO_4$ batteries with two 2 MW wind turbines operating in linked modes [14]. Their strategies of power management were based on concurrent perturbation stochastic approximations (SPSAs) and aimed to minimize battery utilization while producing smoother power profiles along grid interface points. Furthermore, there was 65% power ramp mitigation towards the battery rather than the flywheel.

Li et al. (2021) proposed a mathematical model for a hybrid renewable energy system with nonlinear parts [15]. The reduction in building and operating costs and the slowing down of power consumption were the two considered optimization goals.

The study by Anu Shalini and Sri Revathi (2023) presented a hybrid grid system using battery storage, bidirectional converters, and modified Z power [16]. A hybrid deep learning technique called HDL (CNN-BiLSTM) has been used to estimate the output power of hybrid systems. Using MATLAB/SIMULINK 2.0 software, a 1.5 kW hybrid system was built and the results were verified.

In the laboratory, a model of the proposed system was created and the experimental results were checked. The modeling and experimental results demonstrate that 2.2% total harmonic distortions (THDs) of ANN controllers with spatial vector pulse width modulations (SVPWMs) are within the IEEE 519 standards. The results showed that ANN-SVPWM methods provide lower harmonic currents to networks than the two other controllers combined.

3. Proposed Methodology

In this study, the WPSO algorithm was introduced as part of a power management strategy. The proposal involves the construction of a system model, storage system power, power balancing using the power management strategy, and utilization of the WPSO algorithm for managing renewable energy and the evaluation of results. Figure 2 illustrates the overall schematic of the proposed HES.

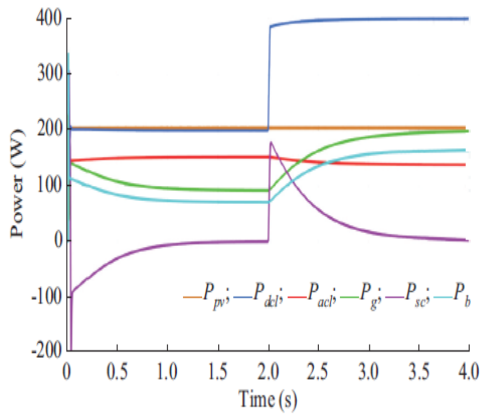

Figure 2. Power of PV, DC load, AC load, utility grid, supercapacitor, and battery with fluctuations in load.

3.1. System Model

The systems in this study were designed to run on both sources (wind and solar) concurrently, along with energy storage systems and backup generators. Hybrid power systems depicted in Figure 1 are standalone systems for producing local PV/wind energy combined with storage systems, for storing surplus energy, and mechanisms to enhance robustness. Diesel generators were also used as backup systems during periods of insufficient power supplies. This section presents the designs and models of multiple energy sources used in the suggested system (including PV generators, wind turbines, and batteries) [17].

3.1.1. Photovoltaic Power Output

The maximum power point (MPP) of PV generator (P_{PV}) power output can be computed as a function of ambient temperature, Tamb, and solar radiation, G (W/m^2), using Equation (1).

$$P_{PV} = \left[P_{STC} \cdot \frac{G}{G_{STC}} * [1 - \gamma \cdot (T_{cell} - T_{cell,STC})]\right] \cdot N_s \cdot Np \quad (1)$$

In the equation, Ppv stands for the photovoltaic (PV) power output at MPP; Ns and Np stand for PV array counts connected in series and parallel, respectively; PSTC, GSTC, and Tcell stand for rated power [18], solar radiation, and cell temperatures in standard test conditions (STC); γ represents the power temperature coefficient at MPP; and Tcell stands for cell temperatures, as expressed in Equation (2).

$$T_{cell} = T_{amb} + \frac{G}{GNOCT} \cdot (NOCT - T_{amb,NOCT}) \quad (2)$$

At nominal operating cell temperature (NOCT), a constant number, GNOCT and $T_{amb,NOCT}$ refer to solar radiation and ambient temperatures, respectively. The manufacturer's STC and NOCT datasheets were compiled to obtain the measurements presented in Table 1.

Table 1. Input parameters.

Parameter	Value	Unit
	Pv (ac-250p/156-60s)	
Rated power	250	Watt
GSTC	1000	Watt/m^2
GNOCT	800	Watt/m^2
NOCT	45	°C
Tamb,NOCT	20	°C
γ	0.043	%/°C
Ns	2	
Np	5	
	Wind turbine (×600)	
Rated power	600	Watt
Vr	12.5	m/s
Vc.in	2.0	m/s
Vc.out	45	m/s
	Battery (BAE Secura 6 PVS 660)	
Capacity	595	Ah
Voltage	12	v
Number of cycle (DOD = 70)	1800	cycle
Efficiency	80	%
Socmin	30	%
Socmax	100	%
Number of batteries	2	
Cost of battery	2110.05	$
	Diesel generator	
Rated power	4	kW

3.1.2. Wind Power Output

Equation (3) was used to compute received power outputs from wind turbine generators (Pw) in the form of wind speed functions V (m/s).

$$p_w = \begin{cases} 0 \quad V < V_{c.in} \; or \; V > V_{c.out} \\ P_r \cdot \frac{V - V_{c.in}}{V_r - V_{c.in}} V_{c.in} \leq V \leq V_r \\ \quad P_r V_r \leq V \leq V_{c.out} \end{cases} \tag{3}$$

where Pr stands for rated turbine powers, and V, V_r, V_(c.in), and V_(c.out)t stand for the speeds of winds, nominal winds, cut-in winds, and cut-out winds, respectively.

3.2. Storage System Power

Lead acid batteries were used in this study because energy storage systems are an essential component of autonomous energy systems. However, if a lead–acid battery model is used, the charge and discharge current limitations, associated with kinetic battery models, must be taken into account.

The maximum charge and discharge currents are expressed as Equations (4) and (5):

$$I_{c,max} = \frac{-k \cdot c \cdot q \; max + k \cdot q1, 0e^{-k, \Delta t} + q \cdot c \cdot k \left(1 - e^{-k, \Delta t}\right)}{1 - e^{-k, \Delta t} + c\left(k \cdot t - 1 + e^{-k, \Delta t}\right)} \tag{4}$$

$$I_{disc,max} = \frac{k \cdot q1, 0e^{-k, \Delta t} + q \cdot c \cdot k \left(1 - e^{-k, \Delta t}\right)}{1 - e^{-k, \Delta t} + c\left(k \cdot t - 1 + e^{-k, \Delta t}\right)} \tag{5}$$

where qmax stands for the maximum battery (Ah) charge where charge transfers need to account for maximum charge/discharge currents, as presented in (6) and (7):

$$I_{ch} = -\min\left(\left|\frac{P_b}{V_b}\right|, \; I_{ch.max}\right) \tag{6}$$

$$I_{disc} = -\min\left(\left|\frac{P_b}{V_b}\right|, \; I_{disc.max}\right) \tag{7}$$

Regarding the state of charge (SOC), in time steps, new capacities can be depicted by Equation (8) during battery charging operations and by Equation (9) for discharging battery operations:

$$q1(1+t) = q1(t) \cdot \, e^{-k, \Delta t} + \frac{q(t) \cdot c \cdot k - 1\left(1 - e^{-k, \Delta t}\right)}{k} - \frac{c\left(k \cdot \Delta t - 1 + e^{-k, \Delta t}\right) \cdot I_{disc}}{k \cdot \eta b} - q_{auto.disc} \cdot \Delta t \tag{8}$$

$$q1(1+t) = q1(t) \cdot \, e^{-k, \Delta t} + \frac{q(t) \cdot c \cdot k - 1\left(1 - e^{-k, \Delta t}\right)}{k} + \frac{c\left(k \cdot \Delta t - 1 + e^{-k, \Delta t}\right) \cdot I_{disc}}{k \cdot \eta b} - q_{auto.disc} \cdot \Delta t \tag{9}$$

where ηb indicates battery efficiencies and $q_{auto.discs}$ stands for the self-discharge/charge of batteries, as computed as Equation (10):

$$q_{auto.disc} = Q \cdot \delta / V_b \tag{10}$$

where δ refers to the daily battery self-discharge rate (presumed to be 2% per day).

A diesel generator in an independent system typically utilized for backup power if the system power supply is inadequate. In this study, the cost incurred by the fuel consumed in the diesel generators was taken into consideration in the optimization problem and the formulation of objective functions. Fuel consumed by DG depends on the amount of energy generated.

3.3. Power Balancing Using Power Management Mechanisms

Power balancing can be carried out utilizing a power management system. The main components of this power management architecture were the generator of the reference current, the power management algorithm, and the regulation of various current converters. The proposed power management framework for grid-connected systems includes the variables PRavg and Prtrans, which refer to averages and transient powers needed for PVs, while ipvr stands for the reference PV currents. For increasing dynamics of DC-link voltages, error coefficients of imbalanced battery current are also included for transient currents. The demand for the required AC load is predicted using a moving average filter (MAF). Under a few defined criteria, the MAF, which is frequently a linear phase finite impulse response (FIR) filter, can function as a perfect LPF. Based on PV generation and load requirements, the power management algorithm (PMA) can determine the operation mode and generate current references. These reference currents then pass through the current control stages before being converted into switching pulses by all of the power converters.

Coupled DC micro grids rely on electricity splits between PV, ESSs, and the AC utility grids in operations. To create a stable system, a full power balance must be maintained. The power balance can be calculated as in Equation (11):

$$P_g(t) + P_{pv}(t) + P_B(t) + P_{sc}(t) - P_l(t) = P_t(t) \tag{11}$$

where $P_g(t) + P_{pv}(t) + P_B(t) + P_{sc}(t) - P_l(t) = P_t(t)$ refers to the respective power of the grid, renewable source, batteries, and supercapacitor unit, correspondingly, and *Pl* (*t*) = *Pdcl*(*t*) + *Pacl*(*t*) shows the total DC and AC load powers. V*dc* represents power balance repairs between productions and demands. There are two aspects to the overall power required at the DC link to balance electricity: the average power component *P¯t*(*t*) and the transient power component *P′t*(*t*). The total power and the corresponding current are given by Equations (12) and (13):

$$P_t(t) = \ddot{P}_t(t) + P'_t = V_{dc} i_t(t) \tag{12}$$

$$i_t(t) = \frac{\ddot{P}_t(t)}{V_{dc}} + \frac{P'_t(t)}{V_{dc}} = \dddot{i}_t(t) + i'_t(t) \tag{13}$$

where *it*(*t*) stands for the operative current, *i¯t*(*t*) refers to average values, and *i′t*(*t*) indicates transient values of operative currents. Operating currents at DC buses are produced by voltage controllers. LPF fixed cut-off frequencies are 6.283 rad/s. The aims of sharing coefficients are to preserve battery SOCs within acceptable ranges for prolonged periods of time and to lessen rates of variations in battery currents throughout common operating states and unanticipated power oscillations. The value of the sharing coefficient is dependent on the battery's SOCb. The reasoning behind the inadequate power mode (IPM) is provided, with U and L standing for the higher and lower SOC levels, respectively. PV power generations are greater than necessary loads, according to sufficient power modes, and excesses are utilized to charge batteries and supercapacitors until they reach their maximum SOC levels, at which time these powers are sent to primary grids.

3.4. WPSO Algorithm for the Utilization of Renewable Energy

The WPSO algorithm is suggested in this study to considerably increase the utilization of renewable energy. The PSO approach was inspired by a common occurrence in the natural kingdom: a flock of birds searching for food. In PSO, a bird is considered as a particle, and the bird group is considered as a particle swarm. The encoding of a particle facilitates the representation of a task scheduler. The important concept of PSO is to derive the best scheduler from all the particles once it has been assessed a specific number of times. The evolving expressions for every particle are detailed in Equations (14) and (15):

$$v_i^{(t+1)} = wv_i^{(t)} + w_1 c_1 r\left(pb_i^{(t)} - x_i^{(t)}\right) + w_2 c_2 R\left(gb_i^{(t)} - x_i^{(t)}\right) \tag{14}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (15)$$

where $v_i^{(t)}$ and $x_i^{(t)}$ indicate the speeds and positions of particle i in the tth iteration, respectively; $pb_i^{(t)}$ and $gb_i^{(t)}$ stand for the global best of the swarm; w_1 and w_2 refer to weight values and the personal best of particle I, respectively; r and R stand for the random values in [0, 1]; and w, c_1 and c_2 indicate the weight parameters.

In PSO, every solution is viewed as a space-based particle. Every particle's location, speed, and fitness value are each individually calculated with the use of an optimum function. Additionally, every particle in the swarm is aware of both its ideal position and actual location, and then uses the following data to change its current position: the best position of the entire swarm; (a) the current position; (b) the current speed; (c) the previous best position. Initial population initialization is carried out. The population is then randomly divided into a number of subpopulations [19]. The issue space is further divided into several virtual subspaces. A hypercube is formed by each subspace. All the dimensions can be divided into slices of the same size for each dimension. As a result, it has subspaces. The particles are then moved into highly efficient subspaces at a slower rate. The final solution obtained using the suggested weight-based optimization method, also known as the WPSO algorithm, is taken as the optimal solution created during optimization. The WPSO method calculates the best and average population member costs, as well as the execution time. In this study, novel time-adaptive PSO has been introduced, depending on the movement patterns, referred to as the movement pattern from WPSO.

- A large V_c value and a lower $|\rho_1|$ value is acceptable during primitive steps to guarantee that the particle continues looking for a higher range (greater V_c) and not towards any particular direction (lower $|\rho_1|$). F = 1 would exhibit a balance between p and g, which would represent a superior choice during the initial steps.
- With the increasing iterations, an increased $|\rho_1|$ is advantageous to sustain the good options identified by the particles find. An increased V_c is still beneficial, as the exploration could still be effective.
- In the final steps of the search, it would be desirable to focus on the best achieved solutions (larger F), which enclose the best known solutions (reduced $|\rho_1|$ and reduced V_c).

The WPSO can be attained by varying all the coefficients (w, c and α) simultaneously. Based on this setting, the values of V_c, ρ_1, and F can be derived through Equation (16):

$$V_c^{(t)} = \begin{cases} V_{max} & t < t_1 \\ \frac{(t-t_1)(V_{min}-V_{max})}{t_2-t_1} + V_{max} & t_1 < t < t_2 \\ V_{min} & t > t_2 \end{cases} \quad (16)$$

Equation (17) represents the function which guarantees that the value of V_c is the maximum at the start and the minimum at the final steps of the search, when it decreases in a linear manner from iteration t_1 to t_2:

$$F^{(t)} = \begin{cases} F_{min} & t < t_1 \\ 1 & t_1 < t < t_2 \\ F_{max} & t > t_1 \end{cases} \quad (17)$$

This equation guarantees that the personal best is given greater consideration, followed by a balanced search that encompasses both the personal and global best, and lastly, the search is centered on the global best. When optimization occurs, the values of the coefficients are altered.

Predictive control approach prototypes for both standalone and grid-connected modes were utilized to manage voltage source converters and maintain the bus voltage's stability while permitting seamless grid synchronization. Multi-segment adaptive droop control power management technology was employed for PV and battery-connected islanded systems. This approach could monitor the system's needs, offer the highest PV power feasible, and modify the operating point [20]. When traditional power systems face peak power shortages, a power management plan attempts to optimize the usage of renewable resources while minimizing demand, focusing on quickly tracking the power converters' working point to increase the dynamic response and lower the pace at which batteries are charged and discharged.

The essential parameters are battery life, cost, and energy resources; cost and time exhibit an inverse relationship with one another. The goal of this technical research was to balance the cost and time factors by employing optimal energy resources for HES.

4. Results and Discussion

Table 2 summarizes the full specifications of the various elements utilized to simulate the proposed HES. For assessing the system performance, the simulation experiment included real-life load demand data and authentic meteorological data, such as wind speed and sun irradiation. The development of this technology will provide electrical power to common building layouts of the National Institute of Technology Calicut (NITC). On a typical day, the climatic data are obtained from weather station records stored at the NITC Campus.

Table 2. Component specifications utilized in the proposed HES.

USP–75 PV Module (www.uslsolar.com) (Accessed on 12 June 2023)		
Parameter	**Variable**	**Value**
Maximum power	P_m	75 W
Voltage @ P_m	V_m	17.1 V
Current @ P_m	I_m	4.39 A
Short circuit current	I_{sc}	4.39 A
Open-circuit voltage	V_{oc}	21.5 V

Power from the PV, DC load, AC load, utility grid, supercapacitor, and battery are shown in Figure 2, together with load fluctuations. The grid current with changes in PV power is shown in Figure 3. The grid current Vs time is provided in Figure 3a and the Magnitude Vs Frequency graph is provided in Figure 3b. The wind speed and sun radiation are depicted in Figure 4. The isolated micro grid is shown in Figure 5. The grid-connected micro grid is illustrated in Figure 6.

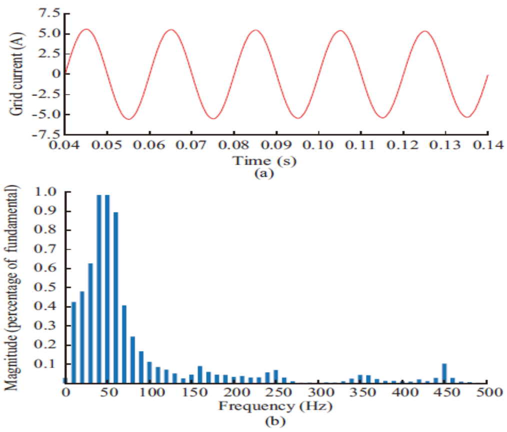

Figure 3. (**a**) Grid current with PV power variation. (**b**) Magnitude with Frequency.

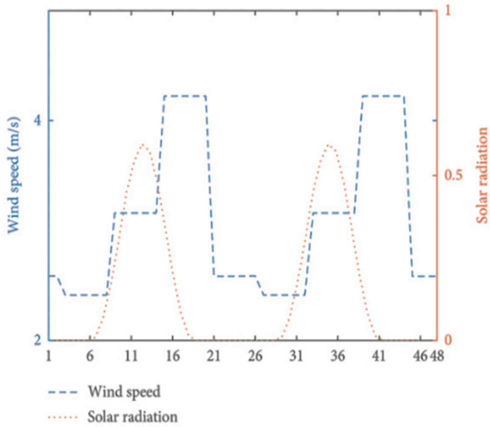

Figure 4. Wind speed and solar radiation.

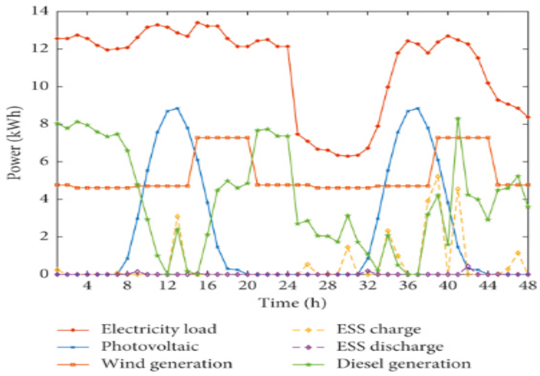

Figure 5. Isolated micro grid.

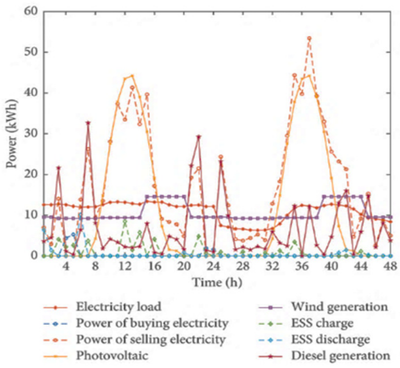

Figure 6. Grid-connected micro grid.

The comparison study between the existing and suggested strategies in terms of cost complexity is illustrated in Figure 7. The cost complexity value is presented in the y-axis, while the techniques are presented on the x-axis. The available techniques using the suggested WPSO algorithm deliver reduced cost complexity for the setting under consideration. The conclusion drawn from the results is that the suggested WPSO improves the HES performance.

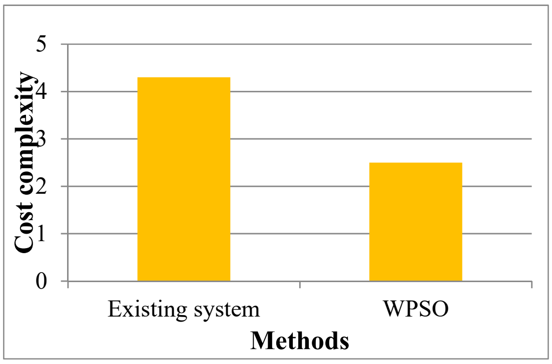

Figure 7. Cost complexity.

5. Conclusions

The WPSO algorithm has been introduced in this study for grid HES (PV, wind turbines, batteries, and diesel generators) and energy management systems. By maximizing usages of generated power from RES and reducing battery power usages, the goal of energy preservation and decreased energy usage costs (i.e., energy of diesel) is attained. In addition to hybrid energy storage systems, unique power management strategies are presented for the regulation of grid-connected PV systems. This strategy ensures fewer power quality attributes with the use of HESSs and crucial goals of bi-directional power flows. The results of the simulation assist in validating the objectives of the suggested strategy, such as rapid DC voltage control, voltage and frequency management, and the treatment of power quality issues, in addition to managing the SOC of storage systems within their limitations. The addition of battery storage systems to solar/wind generators enhances the steadiness of power outputs where the outcomes of simulations indicate efficacies of proposed hybrid alternate energy architecture, as well as overall power management systems. In terms of energy, cost, and battery life savings, the simulation results show that the proposed WPSO surpasses existing algorithms. Particle swarm optimization (PSO) is very slow and time-consuming for real-time implementation and involves high cost estimation. To solve these issues in future enhancement, the use of advanced swarm-intelligence-based optimization algorithms have been introduced for the proposed methodology.

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