Optimal power flow control of hybrid renewable energy system with energy storage: A WOANN strategy

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Citation: Journal of Renewable and Sustainable Energy **11**, 015501 (2019); doi: 10.1063/1.5048446
View online: https://doi.org/10.1063/1.5048446
View Table of Contents: http://aip.scitation.org/toc/rse/11/1
Published by the American Institute of Physics

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Cite as: J. Renewable Sustainable Energy **11**, 015501 (2019); doi: 10.1063/1.5048446
Submitted: 14 July 2018 · Accepted: 17 December 2018 · Published Online: 03 January 2019

View Online Export Citation CrossMark

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ABSTRACT

This paper proposed an optimal control technique for power flow control of hybrid renewable energy systems (HRESs) like a combined photovoltaic and wind turbine system with energy storage. The proposed optimal control technique is the joined execution of both the whale optimization algorithm (WOA) and the artificial neural network (ANN). Here, the ANN learning process has been enhanced by utilizing the WOA optimization process with respect to the minimum error objective function and named as WOANN. The proposed WOANN predicts the required control gain parameters of the HRES to maintain the power flow, based on the active and reactive power variation in the load side. To predict the control gain parameters, the proposed technique considers power balance constraints like renewable energy source accessibility, storage element state of charge, and load side power demand. By using the proposed technique, power flow variations between the source side and the load side and the operational cost of HRES in light of weekly and daily prediction grid electricity prices have been minimized. The proposed technique is implemented in the MATLAB/Simulink working stage, and the effectiveness is analyzed via the comparison analysis using the existing techniques.

I. INTRODUCTION

Recently, energy shortage problems along with high petroleum prices have resulted in severe effects in several technical aspects (Roy and Mandal, 2014). Efficiency improvement of high-power devices, research of alternative energy, investigations of different renewable energy resources, and so forth have been eagerly progressing (Tabart *et al.*, 2018). During the past several decades, a large amount of natural resources of the earth has been unlimitedly consumed, and our living environment has been severely destroyed and polluted (Azharuddin Shamshuddin *et al.*, 2017). Globally, environmental protection concepts and concerns have been generally excited and several new types of renewable resources have been inspected, integrated, and developed in the entire world (Athari and Ardehali, 2016; Luo *et al.*, 2015; and Zheng *et al.*, 2018).

A hybrid power generation/energy storage system (HRES) may combine all different kinds of available renewable energies with available energy storage units (Ma *et al.*, 2015). The required power for the associated demand can be adequately delivered and supplied by the HRES with appropriate control and effective coordination among various subsystems (Suberu *et al.*, 2014). The development of wind power generation systems (WPGSs) results in the reduced cost of generating electricity (Olatomiwa *et al.*, 2016; Trifkovic *et al.*, 2014; and Bocklisch, 2016). With the improvement of semiconductor manufacture technology, photovoltaic (PV) has enhanced efficiency with a lower cost and the installed capacity has become much higher in recent years (Sharafi and ELMekkawy, 2014). However, the PV has lower energy conversion efficiency, lower power density, and higher cost compared to WTGs. Large PV may generate enough supplying isolated loads or delivering energy to a utility grid through dc–ac converters (Behzadi and Niasati, 2015).

Optimal Power Flow (OPF) is a power flow issue to limit an objective function, for example, cost of the generation of active power or the losses in which certain variables are balanced. After obtaining the OPF solution, the implementation of the optimal control variables will convey the system to the "optimum" state (Hassan *et al.*, 2013). In the course of the most recent decades, numerous effective HRES system energy management has been done by several controllers (Zhu et al., 2015). Many researchers have worked with the latest controllers to solve power flow issues such as predictive controllers, sliding mode controllers, and H-infinity controllers for a better steady state and transient response of systems. These control techniques are dependent on complex mathematical analysis. In order to avoid the difficulties in controller designing, intelligent controllers are used (Torreglosa et al., 2015 and Kusakana, 2015).

Different methods on the minimization of real power loss have been carried out in recent research works. The real power loss minimization has been essentially done to meet out the change of the voltage profile using the genetic algorithm (GA) technique. An application of the Fuzzy Logic based Controller (FLC) for inverter voltage and frequency control has worked very well, even after variations in the system parameter and operating conditions (Upadhyay and Sharma, 2014 and Dash and Bajpai, 2015). Here, FLC is implemented in power systems to control power flow, suppress the power fluctuation, and to supply an optimal power to the load (de Matos et al., 2015). In spite of the fact that all the system parameters are known, there may be parameter variations during the operation of the system. So, it is difficult to design the controller parameters and more time is required (Tazvinga et al., 2015). Here, an optimal strategy of combined optimization of the whale optimization algorithm and the artificial neural network (ANN) is proposed. The technique is suggested for the power flow management of the HRES with energy storage. The proposed technique optimizes the gains of the proportional integral (PI) controller based on the minimum error value. The rest of this article is given as follows: the recent research work and the background of the research work are given in Sec. II. The detailed description of the suggested control strategy is clarified in Secs. III and IV. The achievement results and the related discussions of the suggested technique are given in Sec. V, and this paper concludes in Sec. VI.

II. RECENT RESEARCH WORKS: A BRIEF REVIEW

Various research studies have previously existed which were based on the optimal control strategy for power dispatch of the hybrid renewable energy sources using various techniques and various aspects. Some of the works are reviewed here.

Standalone hybrid renewable energy with a hydrogen storage system was illustrated by Khosravi et al. (2018). Wind and solar energies were considered as the renewable energy sources (RESs). For remote area applications, this system was especially suitable, which was mainly focused on hydrogen energy systems on a large scale system. Exergy, energy, and economic analyses were conducted using this system. Rahmani-Andebili et al. (2017) have established the medium-voltage primary electrical distribution system with the aid of energy storage systems (ESS) and renewable energy sources (RESs). Based on the dynamic approach, the daily operation cost of the system was minimized and managed by the local distribution company (DISCO). To deal with the power variability of RESs, a model predictive control (MPC) technique was employed.

Moradi et al. (2018) have investigated the optimal energy scheduling of a standalone microgrid (MG) under system uncertainties. The objective was to enhance the efficiency of utilization of energy and reduce the fuel cost of the system. To accomplish the optimal utilization of renewable resources, the battery storage unit was tested for accuracy. Xiao et al. (2018) have explained a tie-line power flow control of a hybrid MG including photovoltaic (PV) generator, small wind turbines (WTs), and energy storage units (ESUs). In order to determine the local power references of the RES, the central controller sends the proper commands to the local controllers and selects the proper ESU operational mode.

Under unbalanced conditions, a gravitational search algorithm (GSA) based PFC model for energy storage with a smart grid was established by Manuel and Shivkumar (2017). In light of the variation of the system active and reactive power, the power controller parameters were optimized by the GSA technique and the best possible control signals to the voltage source inverter (VSI) system were created. A new combined modified bat search algorithm (MBSA) and artificial neural network (ANN) control of grid-connected HRES were exhibited by Praveen Kumar et al. (2018). MBSA develops the database of the control signals for the disconnected path in light of the power variety amongst source and load sides. In the online way, the achieved dataset was utilized to work the ANN. Talha et al. (2017) have assessed for demand side management the performance of heuristic algorithms included, which are the genetic algorithm (GA) and the artificial fish swarm algorithm (AFSA). The prime centre was to plan machines in a smart home optimally so that the Peak to Average Ratio (PAR) gives decreased electricity cost. Among various DERs, a memory-based genetic algorithm (MGA) optimally shares the power generation task which was explained by Askarzadeh (2018). In the smart grid structure, MGA was used for minimization of the energy production cost. An optimal power flow controller for a utility associated microgrid in view of a real-time self-tuning technique was introduced by Al-Saedi et al. (2013). The motivation behind the finding was to control the active and reactive power flow between the main grid and distributed generation (DG) units. For the active–reactive power (PQ) control technique, the power controller was designed.

A. Background of the research work

The review of the recent research work demonstrates that the power flow control of hybrid renewable energy sources (HRESs) utilizing the energy storage system is an important contributing factor. The unbalanced conditions of HRES such as the frequency drop, environmental dependency, and noisy operation in wind energy systems, harmonics, intermittency, and variation of solar irradiation with the sun intensity are the significant power flow problems in HRES. The drop in frequency can occur due to exceptional overloading of the power system and variation of load levels on the electricity supply system. The natural dependency makes the system extremely unprotected, i.e., lightning strikes, humidity, heat, salinity, dust, and sand. Because of the resonance condition, the harmonics is created over voltage and the system goes to the unstable condition.

These disturbances result in malfunctions, decreased lifetime, and failure of electrical equipment. However, numerous techniques have been actualized for the power flow control. Some of the techniques are the flywheel energy storage system (FESS), proton exchange membrane (PEM), fuel cell (FC), model predictive control (MPC) technique, GA, GSA, ANN, and so on. The flywheel energy storage system displays the constraints like short discharge time. The MPC method can enhance the control execution and inherent compensation for dead times. The drawback found in GSA that it has complex operators and a long computational time. ANN has large complexity of the network structure. GA is very slow and cannot always find the exact solution, but it always finds the best solution. However, the drawbacks like computation complexity and the solutions are not ensured. Despite the fact that the above techniques are utilized for controlling the power flow in HRES, the difficulty of the algorithm is high because of the fact that an increased number of samples are required. Control strategies of renewable energy systems are basically intended to track the demanded power to utilize the energy sources optimally and to regulate the DC bus voltage of the HRES. Also, for avoiding problems such as system loss increment, electric equipment overheating, metering errors, and power interruptions, a high level of power quality is essential. With a specific end goal to conquer this challenge of the power flow management of HRES, an optimal control using advanced technology is required. In related works, few control techniques are exhibited to solve the HRES issue; the previously mentioned drawbacks have inspired to do this research work.

III. CONFIGURATION OF HRES AND PROBLEM FORMULATION

In this section, the HRES connected with the electrical grid is modeled, which comprises a PV array, a wind turbine, and a battery storage unit. The components of the hybrid system are connected by means of converters. Here, the PV array and the wind turbine are utilized for the generation to meet the electrical load. The grid fulfills the need for backup when the demand exceeds the generation. To manage the power flow, the inverter is provided with the proposed control circuit. The schematic diagram of the proposed control structure of the HRES system is outlined in Fig. 1.

The PI controller controls the inverter through the optimization of the evolutionary computing techniques. The objective of utilizing the controller is to enhance the dynamic performance and to maintain the power flow of the grid connected HRES. The modeling of the HRES is given in Sec. III A.

A. Modeling of HRES

The modeling of HRESs such as the PV array, wind turbine, and battery stack is illustrated and discussed. The fully controlled bidirectional converter is utilized to control the power flow among the hybrid system. The net power flow equation is expressed as (Athari and Ardehali 2016)

$$P_{pv}(t) + P_{wind}(t) + P_{battery}(t) - P_{load}(t) = 0, \tag{1}$$

where P_{pv}, P_{wind}, $P_{battery}$, and P_{load} represent the output power of the PV array, the output power of the wind turbine, the output power of the battery, and the electrical load power, respectively. The performance of the HRES is analyzed by the modeling of the individual component.

1. PV array

The performance of the PV model is highly influenced by the weather conditions, particularly, the impact of temperature. Hence, five parameters (α, β, γ, R_s, & a) are acquainted for the non-linear impacts of the fault condition. The expression of the maximum output power generated by the PV module (P_{pv}) is composed as (Yang *et al.*, 2008)

$$P_{pv}(t) = N_s N_p \times \frac{\left[\frac{V_{oc}}{V_t} - \ln\left(\frac{V_{oc}}{V_t} + 0.72\right)\right]}{1 + \frac{V_{oc}}{V_t}} \times \left(1 - \frac{R_s I_{sc}}{V_{oc}}\right) \times I_{sco}\left(\frac{G}{G_o}\right)^{\alpha} \times \frac{V_{oco}}{1 + \beta \ln\left(\frac{G_o}{G}\right)} \cdot \left(\frac{T_o}{T}\right)^{\gamma}, \tag{2}$$

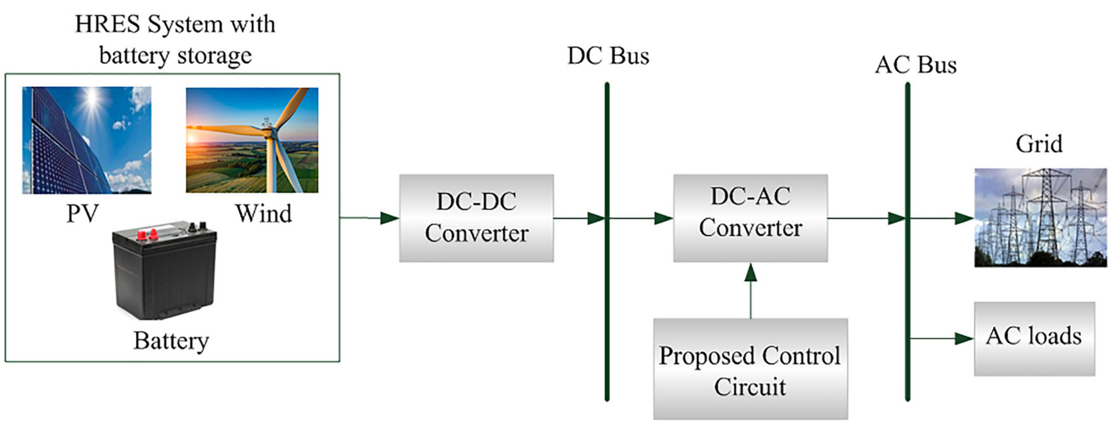

FIG. 1. Proposed control concept of DC and AC bus linked HRES systems with battery storage.

where $V_t = aKT/q$ represents the thermal voltage, a is the ideality factor, K is the Boltzmann constant, T is the temperature of the PV module, and q is the charge of the electron. N_s and N_p are the series and parallel PV modules, respectively. R_s is the series resonant, α represents the photocurrent factor, β is the PV dimensionless coefficient, and γ represents the non-linear factor. In addition, V_{oc} and I_{sc} are the voltage and current of the PV module, respectively.

2. Wind turbine

The wind turbine generates the maximum power based on the local wind speed and the characteristics of the equipment. The expression to determine the maximum output power of the wind turbine is written as (Chen *et al.*, 2017)

$$P_{wind}(t) = \begin{cases} P_r \times \dfrac{v(t) - v_c}{v_r - v_c}, & v_c \le v(t) \le v_r \\ P_r, & v_r \le v(t) \le v_f \\ 0, & v(t) < v_c \, or \, v > v_f, \end{cases} \tag{3}$$

where $v(t)$ represents the hourly wind speed and P_r and v_r are the rated wind power and rated wind speed, respectively. v_c and v_f are the cut-in and cut-off wind speed, respectively.

3. Battery stack

The battery stack is used to store the energy when the generated power is greater than the load. The battery power will be extracted since the generation cannot satisfy the load requirements. Depending upon the charging and discharging state, the current may be positive or negative. Losses may occur in both the states, and hence, the SoC of the battery is expressed as (Wu *et al.*, 2014)

$$SOC(t+1) = SOC(t) \times \left(1 - \frac{\delta \times \Delta t}{24}\right) + \frac{I_{battery}(t) \times \Delta t \times \eta_{battery}}{C_{battery}}, \tag{4}$$

where δ represents the self-discharge rate, $I_{battery}(t)$ is the current rate of the battery at time t, $C_{battery}$ is the available capacity of the battery, and $\eta_{battery}$ is the efficiency of the battery. The output power of the battery for the HRES can be described as

$$P_{battery}(t) = P_{pv}(t) + P_{wind}(t) - \frac{P_{ac\,load}(t)}{\eta_{inv}} - P_{dc\,load}(t), \tag{5}$$

where η_{inv} is the inverter efficiency. The limits of SOC of the battery stack are expressed as

$$SOC_{min} \le SOC(t) \le SOC_{max}. \tag{6}$$

For managing the power flow of the HRES with energy storage, the optimized controller is designed for the converter. The control design of the proposed controller is explained in Sec. III B.

B. Controller design

In this work, the voltage source inverter (VSI) is allocated to interface the HRES framework and the VSI operation is illustrated with six controlled switches. Here, the VSI based pulse width modulation (PWM) is driven by the proposed controllers. The controller enhances the voltage profile between the HRES and the grid at different operating conditions. The PI controller is tuned to reduce the deviation among the active and reactive power. The proposed technique performs this optimization problem in terms of integral squared error (ISE). The PI controller tuned by the proposed techniques is delineated in Fig. 2.

The proposed technique is utilized to reduce the ISE between the reference active and reactive power. The vector connection between the inverter output voltage and the power angle alongside the inductor's reactance decides the flow of the active and reactive power among the sources and AC bus. The scientific relationship for P and Q is given in the following equations:

$$P = \frac{3}{2} \times \frac{VE}{2\omega L} \sin\theta, \tag{7}$$

$$Q = \frac{3}{2} \times \frac{V}{\omega L}(V - E \ \cos\theta). \tag{8}$$

From the above equation, it is found that P is subject to the power angle θ and Q is reliant on the inverter output voltage. Consequently, P and Q can be freely controlled by the proposed control scheme. The ISE is minimized according to the following cost function at various fault conditions.

The objective is expressed as

$$J = \frac{1}{t}\int_0^t \left(e_v(t)^2\right) dt, \tag{9}$$

where J is the cost objective and e_v is the error voltage. The fitness is a function of two control parameters of the proposed PI controllers (K_p *and* K_i). The optimization algorithm used to optimize the control parameters of the PI controller is given in Sec. IV.

IV. PROPOSED WOANN CONTROL STRATEGY

A novel optimization approach is suggested for the power flow control of the HRES with the energy storage. The proposed control scheme is the joined execution of the whale optimization algorithm with ANN (WOANN). Here, the network of the multilayer ANN is trained for the optimized value by utilizing the WOA technique. In the perspective of the error of the active and reactive power, the WOA can find the optimal gain parameters of the proportional integral (PI) controller. The input of the system is the K_p, and K_i values are randomly chosen. The real and reactive power values are the inputs of the algorithm. The error in the system is diminished, and keeping in mind the end goal, optimal power flow management is proficient to tune the parameters of the PI controller. To find the objective function, the steps of the WOA algorithm are cleared up in Sec. IV A.

A. Dataset generation using WOA

The WOA is a newly developed meta-heuristic optimization algorithm proposed by Mirjalili and Lewis (2016) for numeric optimization. The fundamental contrast amongst WOA and

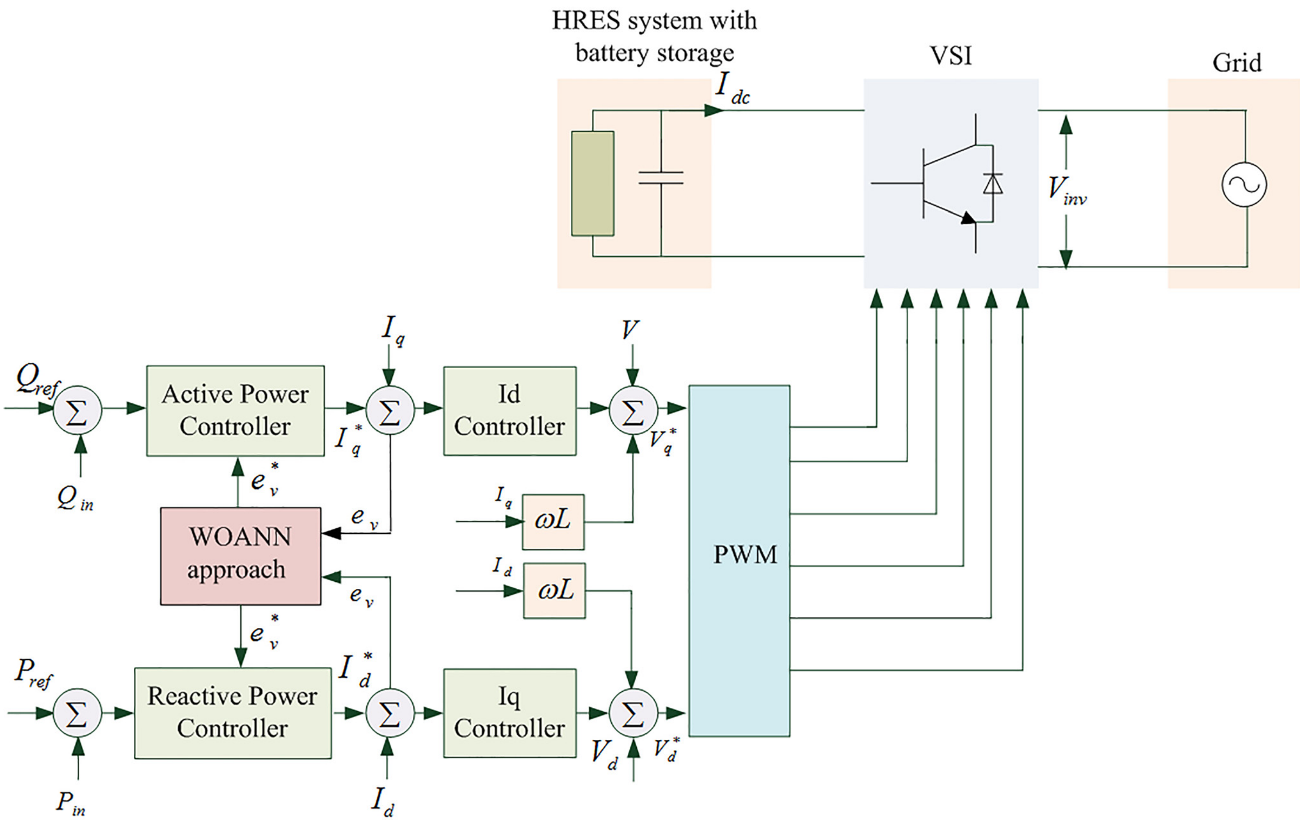

FIG. 2. Structure of the proposed WOANN Controller.

different algorithms is the guidelines that enhance the hopeful arrangements in each progression of streamlining. The WOA is inspired by the bubble-net hunting strategy of humpback whales. In this paper, the WOA is used to train the ANN for the accurate optimization of the controller parameters. The input of the algorithm is the error signal of both the active and the reactive power of the PI controller. The WOA generates the dataset of optimal gain parameters as the output which is used to train the network of ANN. The algorithm steps representing the hunting behaviors of WOA are given as follows:

(i) **Initialization:** Initialize the input parameters such as the error signal of the real power P and reactive power Q values and the output as the optimal PI gain parameters.

(ii) **Random generation:** After the initialization process, randomly generate the PI controller gain parameters such as K_p and K_i

$$RG^i = \begin{bmatrix} K_p^{11}K_i^{11} & K_p^{12}K_i^{12} & \ldots & K_p^{1n}K_i^{1n} \\ K_p^{21}K_i^{21} & K_p^{11}K_i^{11} & \ldots & K_p^{2n}K_i^{2n} \\ \vdots & \vdots & \vdots & \vdots \\ K_p^{m1}K_i^{m1} & K_p^{m2}K_i^{m2} & \ldots & K_p^{mn}K_i^{mn} \end{bmatrix}, \tag{10}$$

where $K_p^{mn}K_i^{mn}$ are the random solutions of PI gain parameters.

(iii) **Evaluation:** The fitness function is evaluated using Eq. (9) as long as the equality and inequality constraints of Eqs. (1) and (6) are known. Here, the objective function *Fit* is to minimize the error function. By utilizing the accompanying condition, the error minimization value is inspected; in an optimization problem, the objective function is derived as follows:

$$\text{Fit} = \min E. \tag{11}$$

Here, $E = P_{ref} - P_I$ for the management of active power and $E = Q_{ref} - Q_I$ for the management of reactive power. E is the error function of the system. Once the minimum objective function is achieved, the process gets optimized and the corresponding parameters K_p and K_i are tuned.

(iv) **Search for the prey:** In the exploration phase, the position of the search agent is updated instead of the best search agent and this behavior can be represented as follows:

$$D = |\vec{C} \times \vec{X}_{rand} - \vec{X}|, \tag{12}$$

$$X(iter + 1) = \vec{X}_{rand} - \vec{A} \times \vec{D}, \tag{13}$$

where *iter* denotes the current iteration and A and C are the coefficient vectors. D indicates the distance of the ith whale to the prey, and $\vec{X}$ specifies the position vector of the whale. $\vec{X}_{rand}$ is the random position vector.

(v) **Encircling prey:** The whale has the capability to recognize the prey location by encircling. The encircling behavior is represented as

$$D = |\vec{C} \times \vec{X}_p(iter) - \vec{X}(iter)|, \tag{14}$$

$$X(iter+1) = \vec{X}_{rand} - \vec{A} \times \vec{D}, \tag{15}$$

where $\vec{X}_p$ specifies the prey vector position. The vectors A and C are represented as

$$\vec{A} = 2\vec{a} \times \vec{r}_1 \times \vec{a}, \tag{16}$$

$$\vec{C} = 2 \times \vec{r}_2, \tag{17}$$

where the component of $\vec{a}$ is linearly decreased over the exploration and exploitation phases. $\vec{r}_1$ and $\vec{r}_2$ are the random vectors in the range of [0, 1].

(vi) **Spiral updating positions:** During the optimization, the whale chooses the updating position based on Eq. (17)

$$\vec{X}(iter+1) = \begin{cases} \vec{X}_p(iter) - \vec{A} \times \vec{D} & if\ p < 0.5 \\ \vec{D} \times e^{bl} \times \cos(2\pi l) + \vec{X}_p(iter) & if\ p \geq 0.5, \end{cases} \tag{18}$$

where p is represented as the random number. The WOA optimizes the given problem by generating a set of random results.

(vii) **Termination:** On the off chance, the maximum count of iterations is achieved which fulfills the stopping criterion once the process is completed. The output of the algorithm is framed as the dataset to prepare the ANN. Else, rehash the process. The output of the algorithm is spoken to as underneath in the active and reactive power generation.

$$\begin{bmatrix} (P^{11}Q^{11}) & \cdots & \cdots & (P^{1n}Q^{1n}) \\ (P^{21}Q^{21}) & \cdots & \cdots & (P^{2n}Q^{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (P^{m1}Q^{m1}) & \cdots & \cdots & (P^{mn}Q^{mn}) \end{bmatrix} = \begin{bmatrix} K_p^{11}K_i^{11} & \cdots & \cdots & K_p^{1n}K_i^{1n} \\ K_p^{21}K_i^{21} & \cdots & \cdots & K_p^{2n}K_i^{2n} \\ \vdots & \vdots & \vdots & \vdots \\ K_p^{m1}K_i^{m1} & \cdots & \cdots & K_p^{mn}K_i^{mn} \end{bmatrix}. \tag{19}$$

The proposed ANN-based power flow management of the HRES scheme is prepared well, and the optimal results are given by the generated output in the online process; these are cleared up in Sec. IV B.

B. Prediction using ANN

The ANN is the model of the artificial human brain fit for adjusting to the changes in the circumstances and adapts rapidly in the right setting (Al-Masri *et al.*, 2015; Das *et al.*, 2014). The ANN comprises an interconnected system of neurons and synapses. The neurons acknowledge inputs and play a major role in the majority of their data inputs, and after that, the outcome experiences a transfer function to deliver an output. The contribution of a neuron is the weighted aggregate of its inputs. The three general layers of the ANN are the input layer, hidden layer, and output layer. The input of the network is the real power (P) and reactive power (Q), and the output of the network is the optimal PI gain parameters. In light of the resource accessibility, the gain parameters, optimal real and reactive power, and their control signals are at first chosen. The number of input nodes in the neural network is 1, the hidden node in the neural network is 50, and the number of output nodes in the neural network is 5. The back propagation algorithm is used for the training technique. The accompanying clarifies the training procedure.

1. Steps for the back propagation learning algorithm

Step 1: Initialize the input, hidden, and output layer weights of the neural network (NN). The input of the network is the real power (P) and reactive power (Q), and the output of the network is the optimal PI gain parameters.

Step 2: The network is learnt according to the input and the corresponding target.

Step 3: The back propagation error of the target u is calculated using accompanying Eq. (20)

$$e(n) = u_{target}(n) - u_{actiual}(n), \tag{20}$$

where $u_{target}(n)$ is the network target of the nth node and $u_{actiual}(n)$ is the current output of the network.

Step 4: The output of the network is determined based on the following equation:

$$u_{actiual}(n) - \alpha_x + \sum_{n=1}^{N} w_{1n} u_{actiual,k}(n), \tag{21}$$

where α_x is the node bias function

$$u_{actiual,k}(n) = \frac{1}{1 + \exp(-w_{1n}u(n) - w_{2n}u(1))}. \tag{22}$$

Step 5: Each neuron of the network is updated by $w_n = w_o + \Delta w$, where w_n is the new weight, w_o is the old weight, and Δw is the change of weight. The change in the weight can be determined by the following equation:

$$\Delta w_k = \delta \times u(n) \times e(n), \tag{23}$$

where δ is the learning rate ranging from 0.2 to 0.5.

Step 6: Repeat the above steps until e gets minimized $e < 0.1$.

Once the ANN training process is finished, the network is prepared well to generate the optimal power flow of the system. By generating the optimal PI gain parameters, the real and reactive power flow of HRES is controlled. The flowchart of the WOANN control technique is illustrated in Fig. 3.

V. RESULTS AND DISCUSSION

The optimal control strategy is implemented on a grid connected HRES with energy storage. The proposed system is

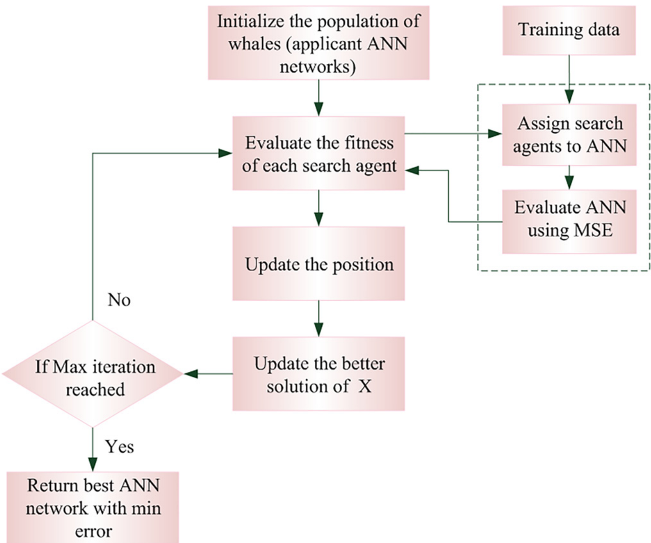

FIG. 3. Flowchart of the proposed WOANN technique for optimal HRES with energy storage.

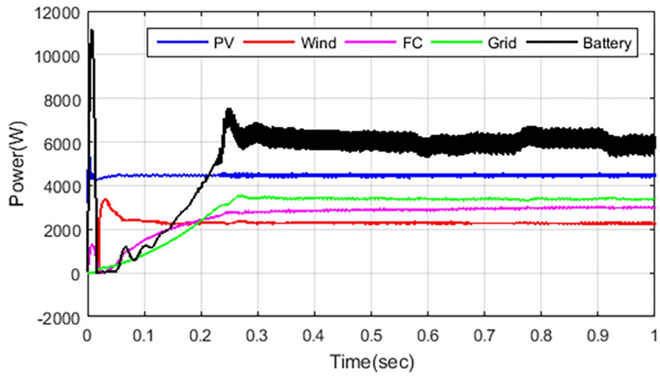

FIG. 4. Analysis of individual power comparison under the load variation condition.

established with the MATLAB/Simulink platform, and their performance is analyzed. In the proposed technique, the hybrid system is integrated with the grid and the variable load. Because of the integration of various conventional and non-conventional hybrid power generation, when the load/demand is fluctuated and in particular, when it exceeds, the grid gets affected. During this condition, the proposed technique optimizes the error signal and provides the optimal control signal for the inverter. The inverter generates the required signal for mitigation of the distortion caused by the non-linear load. Thus, the proposed technique is analyzed in both the cases of variation of load conditions and the zero PV conditions. The overall capacity of sources is tabulated in Table I.

The results of the proposed technique in the two cases are illustrated and discussed in accompanying cases.

A. Case A: Deviation in load conditions

In this case, the proposed technique is analyzed on a hybrid system under the load variation condition. The individual power of the hybrid system is analyzed and implemented. Figure 4 shows the overall analysis of individual power comparison of hybrid systems such as PV, wind, FC, grid, and battery under the load variation condition. The PV power of the proposed technique compensates the deviation when t = 0.22 to 1 s when the generation is 4500 W. The wind power of the proposed technique reaches the high power initially and then comes down to the power condition of 2300 W. The FC power of the proposed technique compensates the deviation when t = 0.15 to 1 s when the generation is 2200 W. The grid power increases from t = 0 to t = 0.25 s and then reaches the constant power at 3500 W. The battery power reaches the power of 7600 W at the instant of 0.22 s and then slowly comes down to constant by the proposed technique. In the overall analysis, the rise time, settling time, and overshoot time of the proposed technique are simulated using MATLAB. Thus, it proves that the proposed technique mitigates the deviated output of each and every power generating source devices.

TABLE I. Overall capacity of the sources.

Sources	Overall capacity (kW)
Wind	3.5
PV	5.5
Battery storage	12
Grid	4
Load	22 (Maximum Range)

The efficiency of the proposed technique is analyzed by comparison with the different techniques of proportional integral (PI), genetic algorithm (GA), particle swarm optimization (PSO), and bat search algorithm (BAT). Figure 5 shows the battery power, individual power, and total power analysis using the different methods. Figure 5(a) shows the comparison analyses of battery power for the different techniques. From the battery power analysis, it is seen that the proposed technique achieves quick response in terms of rise time, settling time, and overshoot time. Figure 5(b) shows the comparison of the positive sequences of the inverter power. The proposed technique overcomes the deviation compared to the different techniques. The total power comparison analysis is shown in Fig. 5(c), which is compared with the above-mentioned different techniques. From the figure, it is observed that the proposed technique achieves the maximum power, which is higher than the different techniques.

B. Case B: Zero PV condition

In case B, the proposed technique is analyzed on the hybrid system under the condition of zero PV power. The output power of each and every power generating source devices of the hybrid system is analyzed and exhibited. Figure 6 shows the overall analysis of individual power comparison of hybrid systems such

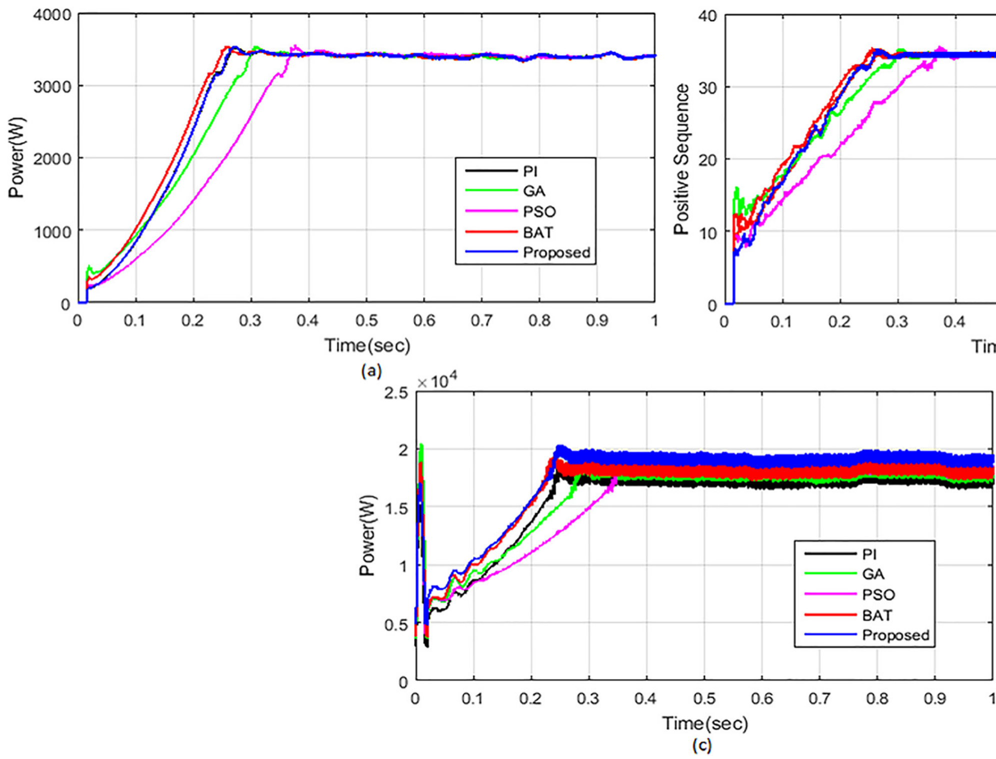

FIG. 5. Comparison analysis of the proposed technique with different techniques in case A of (a) Battery power, (b) Inverter power, and (c) Total power.

as PV, wind, FC, grid, and battery under the load variation condition. The PV power of the proposed technique compensates the deviation when t = 0.22 to 0.7 s at the generation of 4500 W and then comes down to zero value up to 1 s. The wind power of the proposed technique is initially at the high power and then comes down to the constant power of 2300 W. The FC power of the proposed technique compensates the deviation when t = 0.22 to 1 s and the generation is 2500 W. The grid power increases from t = 0 to t = 0.25 s and then reaches the constant power at 3500 W. The battery power reaches the power of 7500 W at the instant of 0.23 s and then slowly comes down to constant in the proposed technique. In the overall analysis, the rise time, settling time, and overshoot time of the proposed technique are analyzed. From the comparison, it is proved that the proposed technique mitigates the deviation of each and every power generating source devices effectively.

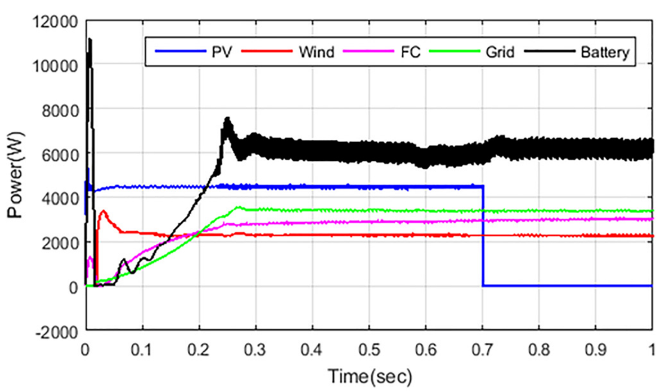

FIG. 6. Analysis of individual power comparison under the zero PV condition.

The efficiency of the proposed technique is analyzed by comparing with the different techniques of PI, GA, PSO, and BAT. Figure 7 shows the analysis of the battery power, inverter power, and total power using the different methods. Figure 7(a) shows the comparison analysis of battery power for the different techniques. From the battery power analysis, it is seen that the proposed technique achieves quick response in terms of rise time, settling time, and overshoot time. Figure 7(b) shows the comparison of the positive sequence of the inverter power. The proposed technique overcomes the deviation optimally compared to the existing techniques. The total power comparison analysis is shown in Fig. 7(c), which is compared with the above-mentioned different techniques. From the figure, it is observed that the proposed technique achieves the maximum power and then slightly decreases to 15 000 W for the instant of 0.7 to 1 s. In both the cases, the proposed technique achieves better response in terms of rise time, settling time, and overshoot time than the compared different techniques. Figure 8 shows the fitness comparison of the real and reactive power for the proposed and the different techniques in both the cases. Figure 8(a) shows the active power comparison at the varying load conditions, and

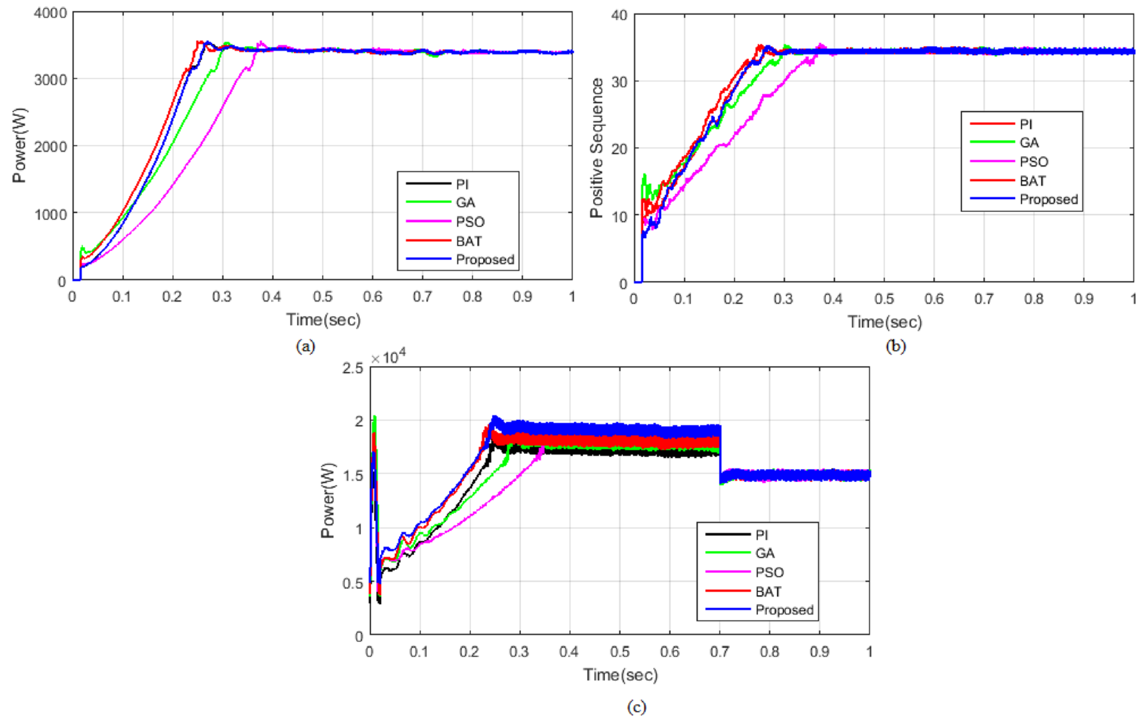

FIG. 7. Comparison analysis of the proposed technique with different techniques in case B of (a) Battery power, (b) Inverter power, and (c) Total power.

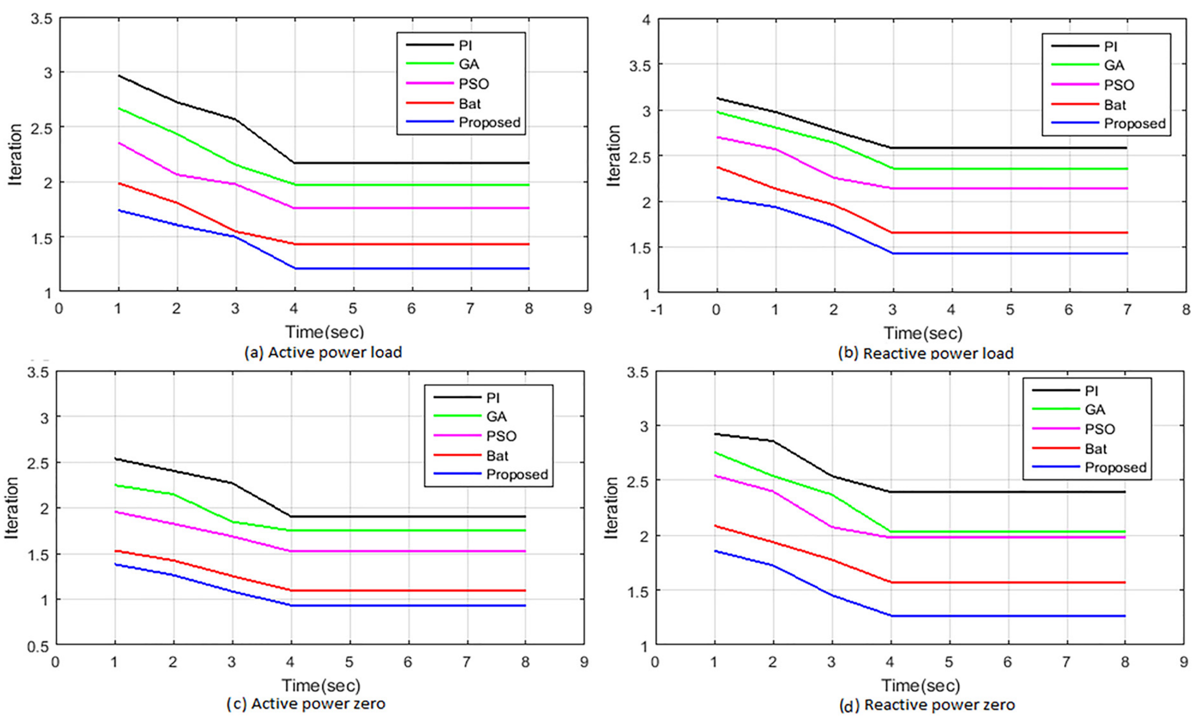

FIG. 8. Comparison graph of real and reactive power in case A and case B conditions.

the fitness is compared with the different techniques for the effectiveness. Similarly, the reactive power comparison at the varying load conditions is shown in Fig. 8(b). For the zero PV condition, the fitness of the active and the reactive power is analyzed in Figs. 8(c) and 8(d). From the overall comparison analysis, the proposed technique achieves the quick response with the minimum execution time and iterations.

VI. CONCLUSION

The proposed technique is successfully used to resolve the optimal power flow problem of the hybrid system. The effectiveness of the proposed technique is executed in the MATLAB/Simulink stage. The proposed system is analyzed for two different cases such as varying load and PV zero conditions. The variation in the load and source conditions caused the deviation of the power signal, which is mitigated by the proposed control technique. The source device of the hybrid system is analyzed in both the cases, and the performance is compared with the different techniques. In both the cases, the proposed technique is proved at improving the power signal in the presence of disturbance conditions. Also, the proposed technique achieves the better dynamic response as far as settling time, rise time, and overshoot time. Moreover, the optimized PI controllers enhance the incorporation of the grid connected hybrid system efficiently. A promising course for future work is surveying the suitability of hybrid storage technologies, for instance, a combination of pumped hydro, thermal, and batteries tending to these optimal power flow issue. Issues identified with mathematical validation, deregulated market constraints, contingency incorporation, and renewable source integration are most recent difficulties for future optimal power flow issues. Furthermore, other better strategies may likewise be considered for further investigation.

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