engineering proceedings

Proceeding Paper

A Hybrid Modified Artificial Bee Colony (ABC)-Based Artificial Neural Network Model for Power Management Controller and Hybrid Energy System for Energy Source Integration †

Udayakumar Ramanathan [1,*], Sugumar Rajendran [2], Devi Thiyagarajan [3] and Elankavi Rajendran [4]

1 Department of CS & IT, Kalinga University, Naya Raipur 492101, Chhattisgarh, India
2 Institute of CSE, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai 600077, Tamilnadu, India; sugu16@gmail.com
3 Department of Computer Science & Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai 600077, Tamilnadu, India; devi.janu@gmail.com
4 Department of Computer Science and Engineering, Siddharth Institute of Engineering & Technology, Tirupati District, Puttur 517583, Andhra Pradesh, India; kavirajcse@gmail.com
* Correspondence: deancsit@kalingauniversity.ac.in or rsukumar2007@gmail.com
† Presented at the International Conference on Recent Advances on Science and Engineering, Dubai, United Arab Emirates, 4–5 October 2023.

Abstract: Small MGS (microgrid systems) are capable of decreasing energy losses. Long-distance power transmission lines are constructed by integrating distributed power sources with energy storage subsystems, which is the current trend in the development of RES (renewable energy sources). Although energies produced by RES do not cause pollution, they are stochastic and hence challenging to manage. This disadvantage makes high penetration of RES risky for the stability, dependability, and power quality of main electrical grids. The energies obtained from RES must thus be integrated in the best possible way. To provide maximum energy sustainability and best energy usage, hybrid energy systems must manage energy efficiently. In order to improve power management and make better use of RES, this study offers a hybrid energy power management controller based on hybrid MABC (modified artificial bee colony) and ANN (artificial neural network) for MGS, PVS (photovoltaic system), and WT (wind turbine). Controlling power flows between grids and energy sources is the suggested approach for power control. D/R (demands/responses), customer reactions, offering priorities, D/R properties like COE (cost of energies), and sizes (lengths) are considered in this work. Along with current techniques, a suggested model is implemented in the MATLAB/Simulink platform.

Keywords: microgrid (MG); photovoltaic (PV); wind turbine (WT); modified artificial bee colony (MABC); artificial neural network (ANN)

Citation: Ramanathan, U.; Rajendran, S.; Thiyagarajan, D.; Rajendran, E. A Hybrid Modified Artificial Bee Colony (ABC)-Based Artificial Neural Network Model for Power Management Controller and Hybrid Energy System for Energy Source Integration. *Eng. Proc.* **2023**, *59*, 35. https://doi.org/10.3390/engproc2023059035

Academic Editors: Nithesh Naik, Rajiv Selvam, Pavan Hiremath, Suhas Kowshik CS and Ritesh Ramakrishna Bhat

Published: 12 December 2023

1. Introduction

The population is expected to increase by 2 billion by 2040. This explosive population growth is mostly concentrated in parts of Africa, India, and developing nations. This has a significant impact on the demand for energies that are forecasted to play an important role in future power schemes. MGS are unique systems of grids that incorporate mixtures of dispersed production and power electronics [1]. It is assumed that use of MGS with improved performance could satisfy energy demands in India.

MGS are promising smart grids that have active low-voltage networks made up of loads, RES, and distributed generating units that can fully use RES to fulfil load demands [2]. The primary energy source in India, photovoltaic (PV) energy generation, is the subject of study [3]. For the year 2016, it was stipulated that the availability of wind and PV resources were complementary. This demonstrated the urgent need to enhance energy resources in order to accelerate the usage of RES. In this study effort, PV/wind integration is therefore suggested [4]. The new energy management system should be re-evaluated based on the following principles since integrated hybrid energy systems differ significantly from traditional power systems:

1. The integrated hybrid energy system's energy management issue is challenging due to the system's several MGs made up of different distributed energy resources [5]. A hierarchical system may be proposed to solve the issue.
2. Due to the presence of several RES and storage units, the integrated hybrid energy system exhibits complex hybrid behaviors, such as continuous dynamic behaviors, event-driven multi-mode switching behaviors, and interactions with one another [6].
3. Due to the unpredictable RES and "plug-and-play" operating style of some distributed generating units, the operational status of the integrated hybrid energy system is unknown. As a result, the integrated hybrid energy system's energy management system requires a high level of intelligence and flexibility to respond to changing operational conditions.

There is now considerable interest in the usage of MGS because of the huge rise of DG (distributed generation), particularly RES. In order to regulate the voltage distribution level and provide electricity or heat to a collection of local loads, MGS combine several DG resources [7]. Hence, dynamic interplays between load demands and RES with stability and quality are critical concerns [8], and managing energy flows in hybrid systems is critical to increasing the system's operating life and guaranteeing consistent energy flows.

This study offers a hybrid energy system with a power management controller employing hybrid MABC-based ANN for improved power management and better utility of RES. The remaining parts of this paper are: Section 2 discusses some of the most modern power management control methods used in hybrid energy systems. Section 3 details recommended approaches and methodologies, with findings and discussion in Section 4. This work concludes in Section 5.

2. Literature Review

This section reviews some of the recent techniques for energy management systems and hybrid energy systems for energy source integration in microgrid applications.

A determinist energy management system for microgrids was presented by Kanchev et al. [9], which included gas microturbines and sophisticated PVS generators with embedded storage units. Power plans were based on load forecasts and power production predictions of PVS. Centralized and local management were interconnected while managing these hybrid sources. Zhou et al. [10] presented a CESS (composite energy storage system) that included both high-density storage batteries and high-powered ultracapacitors. To demonstrate the viability of the suggested strategy, the results were shown. The SEMA (smart energy management algorithm) by Aktas et al. [11] for HESS (hybrid energy storage systems) received power from 3-phase 4-wire connected PVS grids. Yang et al. [12] developed a novel EMS (energy management system) approach to achieve FTF (flexible time frame) DER schedules linked with single time intervals of OPF (optimum power flow)-based distributions. The MGS EMS technology was tested using modified IEEE systems with 34 and 123 nodes. A general management technique was presented by Molderink et al. [13], which was relevant to the majority of domestic technologies, situations, and optimization goals.

Aghajani et al. [14] employed the MOPSO (multi-objective particle swarm optimization) approach for the management and distribution of energies in MGS. Based on multi-objective optimization, Zhang et al. [15] developed the CCHP (combined cooling, heating, and power) MGS model, which improved energy system efficiency and alleviated environmental difficulties caused by animal excrement.

Indragandhi et al. [16] maintained battery SOC (state of charge) while making the most use of RES. Additionally, the lowest rates for power exchange between AC and DC MGS were determined under the proposed system. The outcomes demonstrated that MOPSO generated positive results, and the proposed solutions were the best options to boost the usage of electric energy in rural areas.

3. Proposed Methodology

In order to improve power management and make better use of RES, this study offers a hybrid energy system with a power management controller technique encompassing MABC and ANN to generate a hybrid approach. PVS, WT, and storage systems were considered for MGS. This work recommends control of power flows between MGS and energy sources, considering D/R, responses of customers, offering priorities, D/R magnitudes, lengths, and minimum COE.

3.1. Problem Formulation

MGS are regarded as ES (energy resources), both dispatchable and non-dispatchable resources. WT and PVS are non-dispatchable resources, whereas MT represents a dispatchable resource. The EWH and D/R/loads are regarded as ES sources. The following Equation (1) is listed as the paper's objective:

$$O_f = min\sum_{\delta}^{N} \Delta_\delta \left(C_\delta^{ND} + C_\delta^{D} + C_\delta^{\mathrm{ES}-} - C_\delta^{L} - C_\delta^{\mathrm{ES}} + \psi_\delta \right) \quad (1)$$

where

$N \rightarrow$ time period of simulations
$C_\delta^{ND} \rightarrow$ COE generated by non-dispatchable resources
$C_\delta^{D} \rightarrow$ COE produced by dispatchable resources
$C_\delta^{\mathrm{ES}-} \rightarrow$ Cost of energy generation by ES in charging mode
$C_\delta^{\mathrm{ES}+} \rightarrow$ Cost of energy generation by ES while in charging mode
$C_\delta^{L} \rightarrow$ COE during responsive load consumptions
$\psi\delta \rightarrow$ Penalty for MG operators in time period δ

The entire production cost is reduced using the aforementioned equation while ensuring that generation resource limits are met. Target functions considered MGS operators to avoid undelivered electricity to NRLs, including penalty costs. These expenses may all be computed using the formulas below. Using the following Equation (2), the costs of energies produced by non-dispatchable resources are computed.

$$C_\delta^{ND} = \sum_{i=1}^{N_{nd}} P_\delta^{i,ND} \left(\pi_\delta^{i,ND} \right) \quad (2)$$

The equations given above assist in computing dispatchable/non-dispatchable resource costs. The parameters for Equation (4) are listed below. Next, the costs of loads and generation by ES are calculated. The cost of energy required by a responsive load was calculated using the following Equation (3):

$$C_\delta^{L} = \sum_{i=1}^{N_L} P_\delta^{i,L} \left(\pi_\delta^{ik,L} \right) \quad (3)$$

Based on equations above, $\pi\delta i$, *ND* and $\pi\delta i$, *D* refer to the *i*-th non-dispatchable and dispatchable resources, respectively; *Pδi,ND* and *Pδi,D* represent the power generated by the *i*-th non-dispatchable and dispatchable resources, respectively; and *NND* and *ND imply* counts of non-dispatchable and dispatchable resources in MGS, respectively. Moreover, COE consumed by ES are evaluated using Equations (4)–(6) given below:

$$C_\delta^{ES+} = \sum_{i=1}^{N_{ES}} P_\delta^{i,ES+} \left(\pi_\delta^{i,ES+} + X_\delta^{ES} \right) \quad (4)$$

$$C_{\delta}^{ES-} = \sum_{i=1}^{N_{ES}} P_{\delta}^{i,ES-} . \pi_{\delta}^{i,ES-} \left(1 - X_{\delta}^{ES}\right) \tag{5}$$

$$\psi_{\delta} = \pi_{\delta}^{UP} . P_{\delta}^{i,UP} \tag{6}$$

where π_{δ}^{UP} represents offer prices when systems encounter UP and $P_{\delta}^{i,UP}$ stands for power quantity not supplied by MGS. X_{δ}^{ES} denotes the status of ES operational mode. $X_{\delta}^{ES} = 0$ when ES are in discharging mode and $X_{\delta}^{ES} = 1$ when in charging mode. $\pi_{\delta}^{i,ND}$, $\pi_{\delta}^{i,D}$, $\pi_{\delta}^{i,L}$, and $\pi_{\delta}^{i,ES}$ are evaluated values where constraints are analyzed for evaluating and determining objective functions.

3.2. Constraints

Constraints of equalities and inequalities can be determined.

3.2.1. Equality Constraints

Equations (7) and (8) depict power balances:

$$\sum_{i=1}^{N_{ND}} P_{\delta}^{i,ND} + \sum_{i=1}^{N_{N}} P_{\delta}^{i,D} + \sum_{i=1}^{N_{ES}} P_{\delta}^{i,ES-} \left(1 - X_{\delta}^{i,ES}\right) + P_{\delta}^{UP} \tag{7}$$

$$= \sum_{i=1}^{N_{L}} P_{\delta}^{i,L} + \sum_{i=1}^{N_{ES}} P_{\delta}^{i,ES+} \left(X_{\delta}^{i,ES}\right) + P_{\delta}^{NRL} \tag{8}$$

3.2.2. Inequality Constraints

Equation (9) depicts the inequality constraints of non-dispatchable resources:

$$0 \leq \sum_{i=1}^{N_{ND}} P_{\delta}^{i,ND} \leq P_{\delta}^{m,ND} \tag{9}$$

where $P_{\delta}^{m,ND}$ represents the max. power generated in non-dispatchable units within time period δ, while other constraints are based on [17] and hence electricity quantities consumed by consumers need to be equal to the total EGP consumed during the functioning of normal systems. ANN and MABC are used in this case to obtain the best results. The next section provides a thorough explanation of the suggested technique.

3.3. Hybrid Methods for Optimal Energy Management of MGS

This paper proposes a hybrid control strategy for MGS energy management using distribution system resources. The hybrid approach combines the MABC and ANN algorithms. In this case, MGS consist of PVS, WT, and storage systems. ANN first forecasts PVS, WT, MT, and battery needs over 24 h intervals. The forecasted numbers are then sent into BFOA to obtain the optimal outcomes for MGS power management [18].

3.4. Modeling Energy Systems for Wind and Solar PVS

3.4.1. Modeling Power Outputs from Solar PVS Generators

Power outputs are affected by environmental factors and the solar PVS panel's characteristics. To model these variable solar irradiations, Weibull distributions or Beta distributions can be used [19]. This work utilizes Beta distributions [20], and parameters of Beta models may be computed using historical data for places and times, as in Equations (10) and (11):

$$\alpha = \mu \left(\frac{(1-\mu)\mu}{\sigma} - 1 \right) \tag{10}$$

$$\beta = (1-\mu)\left(\frac{(1-\mu)\mu}{\sigma} - 1\right) \quad (11)$$

The related PDF (probability density function), f(s), can be depicted as Equation (12):

$$f(s_i) = \frac{s(1-s_i)}{\Gamma(\alpha)\Gamma(\beta)}\Gamma(\alpha+\beta) \quad (12)$$

The probability of solar irradiance during specific hours is computed using Equation (13):

$$P = [S = s_i] = \int_{s_i,min}^{s_i,max} f(\zeta).d\zeta \quad (13)$$

The solar PVS power panel's output is computed using Equation (14):

$$(P_{mp}) = \frac{s}{s_{ref}} P_{mp,ref}[1 + (T - T_{ref}) \quad (14)$$

3.4.2. Power Output Modeling of WEG (Wind Energy Generators)

Wind speed dispersions determine the efficacy and feasibility of wind power plants. If wind speed is known, the potential energy and generated power output can be estimated and Weibull distributions can be used to explain illogical behaviors of wind speeds (v) [21], expressed by Equation (15):

$$f(v) = \frac{k}{\alpha}\left(\frac{v}{\alpha}\right)^{k-1}\exp\left[\left(\frac{v}{\alpha}\right)^{k}\right] \quad (15)$$

where v > 0, k > 0, and α > 0. k and α can be calculated using means (v_m) and the standard deviation (σ) of wind speeds can be determined, as depicted below in Equations (16)–(19):

$$v_m = \frac{1}{n}\left\{\sum_{i=1}^{n} v_i\right\} \quad (16)$$

$$v = [\frac{1}{n-1}\sum_{i=1}^{n}(v_i - v_m)^2]^{0.5} \quad (17)$$

$$\alpha = \frac{v_m}{\Gamma\left(1+\frac{1}{k}\right)} \quad (18)$$

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.086} \quad (19)$$

Figure 1 shows that the outputs of wind generators (P_w) are a function of wind speed, as expressed by Equation (20):

$$P_w = \begin{cases} 0, & v \le v_{ci} \\ K_{iv} + K_{2v}, & v_{ci} < v < v_r \; and \; P_r, \; v_r < v < v_{co} \\ 0, & v \ge v_{co} \end{cases} \quad (20)$$

where $K_1 = \frac{P_r}{v_r - v_{ci}}$ and $K_2 = -K_1 v_{ci}$ The PDF can be expressed using Equation (21):

$$P(P_{w,i} = P_r) = P(v_r \le v < v_{co}) = \int_{v_r}^{v_{co}} f(v)dv \quad (21)$$

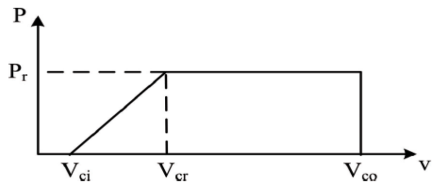

Figure 1. Output of wind power as a function of wind speed.

3.5. Prediction of Load Demand Using ANN

ANN uses artificial neurons to replicate those in the human brain and are illustrations of internal connections receiving a variety of inputs. The neuron's outputs are affected by how the ANN is stimulated. Examples, often known as training examples, are used for learning. The ANN structure shown in Figure 2 consists of input, hidden, and output layers. Backpropagation is used while training the ANN and is explained below.

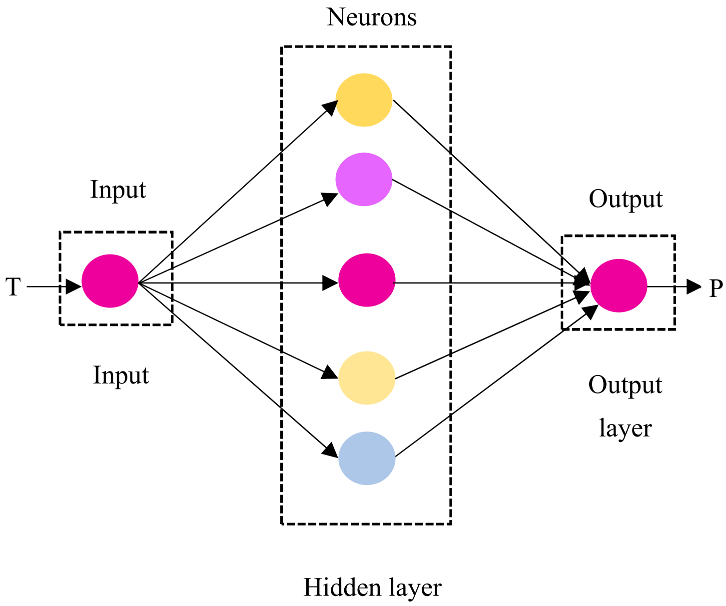

Figure 2. ANN structure based Power output of wind speed.

Algorithmic steps of backpropagation:
Step 1: In Step 1, the weights of the neural network's layers are initialized. In this scenario, the network's inputs are time periods, T, and the outputs are power deficiencies, $P_{WT}(t)$.
Step 2: The second stage is to adapt the network to the inputs and their associated targets.
Step 3: Backpropagation errors of targets $P_{WT}(1)$, $P_{WT}(2)$, and $P_{WT}(n)$ are computed, as mentioned in Equation (22):

$$\begin{pmatrix} BP^{1}_{error} = P_{WT}(1)^{NN(tar)} - P_{WT}(1)^{NN(out)} \\ BP^{2}_{error} = P_{WT}(2)^{NN(tar)} - P_{WT}(2)^{NN(out)} \\ BP^{n}_{error} = P_{WT}(n)^{NN(tar)} - P_{WT}(n)^{NN(out)} \end{pmatrix} \tag{22}$$

where $P_{WT}(n)^{NN(tar)}$ implies the network target of the n-th node and $P_{WT}(n)^{NN(out)}$ stands for the network's current outputs.
Step 4: The network's outputs are obtained using Equation (23):

$$\begin{pmatrix} P_{wt}(1)^{NN(k)} = \left(\frac{1}{1+\exp(-w_{1n}PWT(1)-w_{2n}PWT(2))}\right) \\ P_{wt}(2)^{NN(k)} = \left(\frac{1}{1+\exp(-w_{1n}PWT(2)-w_{2n}PWT(n))}\right) \\ P_{wt}(n)^{NN(k)} = \left(\frac{1}{1+\exp(-w_{1n}PWT(n)-w_{2n}PWT(1))}\right) \end{pmatrix} \tag{23}$$

where $\alpha 1$, $\alpha 2$, and αn represent the bias functions of nodes 1, 2, and n, respectively, as given in Equation (24):

$$\left(\begin{array}{l} P_{wt}(1)^{NN(k)} = \left(\frac{1}{1+\exp(-w_{1n}PWT(1)-w_{2n}PWT(2))}\right) \\ P_{wt}(2)^{NN(k)} = \left(\frac{1}{1+\exp(-w_{1n}PWT(2)-w_{2n}PWT(n))}\right) \\ P_{wt}(n)^{NN(k)} = \left(\frac{1}{1+\exp(-w_{1n}PWT(n)-w_{2n}PWT(1))}\right) \end{array}\right) \tag{24}$$

Step 5: The new weights of the network's neurons are updated using $wnew = wold + \Delta w$. Where $wnew$ stands for new weights, $wold$ implies previous weights, and Δw represents change in the weights of outputs, which are determined using Equation (25):

$$\left(\begin{array}{l} \Delta w_1 = \delta.P_{wt}(1).BP^1_{error} \\ \Delta w_2 = \delta.P_{wt}(2).BP^2_{error} \\ \Delta w_k = \delta.P_{wt}(n).BP^n_{error} \end{array}\right) \tag{25}$$

where δ stands for learning rates (0.2–0.5).
Step 6: The steps above are iterated until $BPerror$ is minimized to $BPerror < 0.1$.

Neural networks are well trained to recognize power demands according to input time intervals after training procedures are complete. MABC optimizes the management of MGS based on the network's outputs. PVS power requirements are also assessed for a whole day. The next section provides an explanation of the MABC algorithm.

MABC Algorithm

A newly developed optimization method, called the ABC algorithm, imitates the clever foraging behavior of honey bees [22]. Honey bee swarms are groups that work to complete tasks co-operatively. The ABC algorithm uses worker, observer, and scout bees in its executions, which search for food based on their memory near the food source while also notifying spectator bees about these food sources. The observation bees typically choose the greatest food sources uncovered by the bees. The chances that observing bees will pick better quality (fitness) food sources are substantially greater than the possibility that they would choose lower quality food. The scout bees descend from limited counts of scout bees who leave their food sources to search for new sources [23].

ABC generates random distributions of SN solutions (food sources). Swarm number is abbreviated as SN. Let the i-th swarm solution be represented as $Xi = \{xi,1, xi,2, \ldots, xi,D\}$, where D represents the dimension size. Each employed bee, Xi, creates a fresh candidate solution, Vi, based on its neighbors, which is depicted as Equation (26):

$$v_{i,j} = x_{i,j} + \Phi_{i,j}.\left(x_{i,j} - x_{k,j}\right) \tag{26}$$

where Xk represents random candidate solutions $(i = k)$, j implies the random dimensionality index chosen from sets {1, 2, . . . , D}, and $\Phi i,j$ stands for random numbers within the interval [−1, 1]. Following the development of a new candidate solution, Vi, greedy selections are used. If Vi's fitness value is greater than that of its parent, Xi is updated; otherwise, Xi is left alone. This probabilistic selection really employs the roulette wheel selection method given in Equation (27):

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{27}$$

here fit_i stands for the fitness value of the swarm's i-th solution. The chances of selecting the i-th food source grows with the quality of solutions. If positions cannot be enhanced after specific cycle counts, or limits, food sources are surrendered. Assuming Xi is the abandoned supply, scout bees identify new food sources to replace Xi using Equation (28):

$$x_{i,j} = lb_j + rand(0,1).(ub_j - lb_j) \tag{28}$$

where lb and ub are the lower and upper limits of the *j*-th dimension, respectively; and rand(0, 1) implies random integers generated between [0, 1] using a normal distribution.

ABC, a relatively recent optimization approach, demonstrated its ability to compete with prior population-based algorithms. The ABC solution search equation is still insufficient; it performs well for exploration but poorly for exploitation. To improve exploitation, better solutions should be offered based on the supposition that bees only examine the best solutions from previous iterations. This idea was influenced by differential evolution (DE).

The ABC solution search equation must be fully used and balanced in order to apply the suggested solution search methodology. Distribution probability (DP) was introduced and new search mechanisms were obtained.

(a) Modification of Search Space

DE has been demonstrated to be a versatile evolutionary algorithm addressing a variety of optimization issues in practical settings. It operates in a manner similar to evolutionary algorithms. After initiation, DE begins cycles of mutations, crossovers, and selections wherein distinct evolutionary algorithms have distinct mutation techniques, differentiating them from one another. A mutation is described in Equation (29):

$$DE/best/1: \ V_i = X_{best} + F(X_{r1} - X_{r2}) \tag{29}$$

where i $\frac{1}{4}$ f1,2, _ _ _, SNg and r1 and r2 are mutually exclusive random integer indices chosen from f1,2, _ _ _, SNg. Scaling factors or amplification factors are +ve real numbers less than 1.0 and control the population's evolving speed. Search Equation (30) is based on the ABC property and variation DE methods, depicted as:

$$ABC/best/\ 1: \ v_{i,j} = X_{best,\ j} + \phi_{i,j}(X_{r1,j} - X_{r2,j}) \tag{30}$$

where the indices r1 and r2 are mutually exclusive integers randomly chosen from {1,2, _ _ _, SN}, and differ from base index i; Xbest implies the best individual vectors with the best fitness in a current population; $j \in \{1, 2, \ldots, n\}$ is a randomly chosen index; $\phi_{i,j}$ is a random number in the range [−1, 1]. The coefficient $\phi_{i,j}$ is a uniform random number in the range [−1, 1] and $\phi_{k,j}$ stands for random individuals in the population. The solution searches therefore became dominant and sufficiently random for investigations. To put it another way, solution search equations perform admirably for explorations but dreadfully for exploitations. In other words, ABC produces low convergence because it excels at exploration but struggles with exploitation. Meanwhile, ABC/best/1 cannot escape early convergences since it is brilliant at exploitation but not so good at exploration. A new search mechanism incorporating the chosen probability, P, to resolve this paradox and balance investigations of the solution search Equation (28) and application of the modified solution search Equation (30) was proposed.

(b) Adjusting the Distribution Probability (DP)

The parameter DP is crucial in maintaining a balance between the candidate solution search's exploration and exploitation. When P = 0, only Equation (30) is in operation. The investigation of Equation (28) will grow proportionally when P rises from 0 to 1. P should not, however, be set too high, as a high value of P can make the algorithm less effective. As a result, the distribution probability parameter (DP) must be adjusted. The impact of this parameter was investigated employing 6 distinct 30-dimensional test functions. Since, all tests had issues with minimization, the final results were the best. The proposed method, most crucially, may achieve a balance between exploration and exploitation.

4. Results and Discussion

The output of the suggested method over MG is shown in this section. The hybrid energy system taken into consideration in the study was subjected to the simulated RES (RERs), i.e., wind and solar energy systems and load needs. The suggested approach was used to calculate WT, PVS, MT, and ES levels of power across 24 h periods. Comparative analyses of generated powers, SOC, and costs of MGS are depicted in the following figures.

Figure 3 shows that the battery is first charged for durations of 1–12 h. At the conclusion of this procedure, the instant SOC is determined. Battery power is used in discharging mode between times t = 12 and t = 16 h. Similarly, throughout the remaining times, ES are assessed for supplying the fractions of power deficiency while the suggested approach is used in charging mode and keeps achieving SOC.

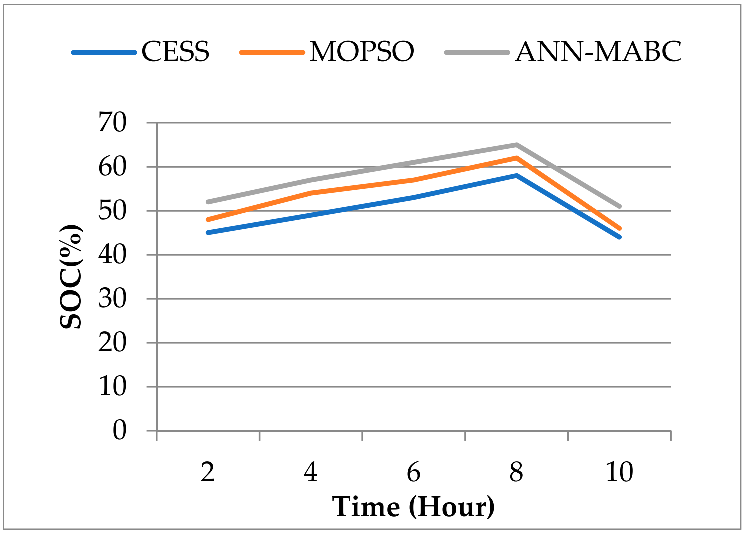

Figure 3. Comparative results of SOC using the proposed and existing methods.

Figure 4 illustrates the costs of the system for both the suggested and current approaches. Additionally, the suggested method's maximum generated and used powers are examined and compared to those of existing approaches. The overall cost of generating power is then assessed. The calculation times, total generation costs, and fitness graphs were assessed and compared with current approaches in order to gauge the success of the suggested method.

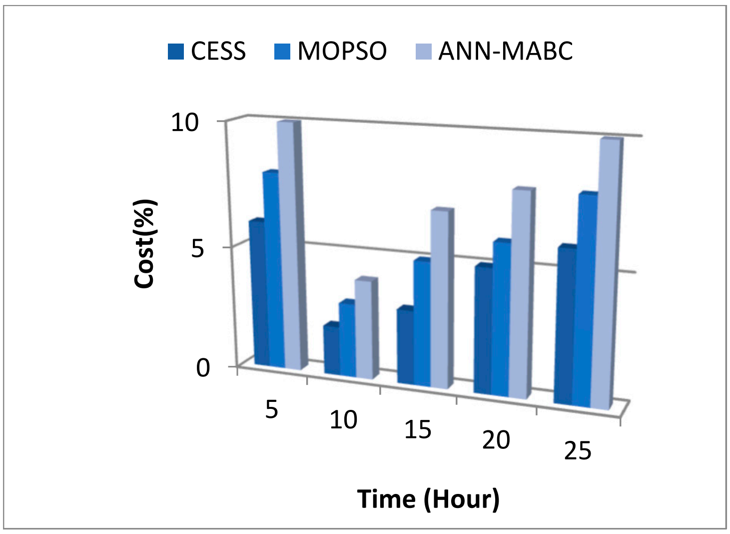

Figure 4. Comparison of costs between the proposed and existing methods.

Figure 5 illustrates the comparison of PVS-generated power results. According to the study above, even with the suggested algorithms, the system was capable of meeting all power needs from the load during normal operation The ES then enter charging mode at predefined times. Using the provided approach and appropriate MT selection, ES are operated in charging mode in EMS.

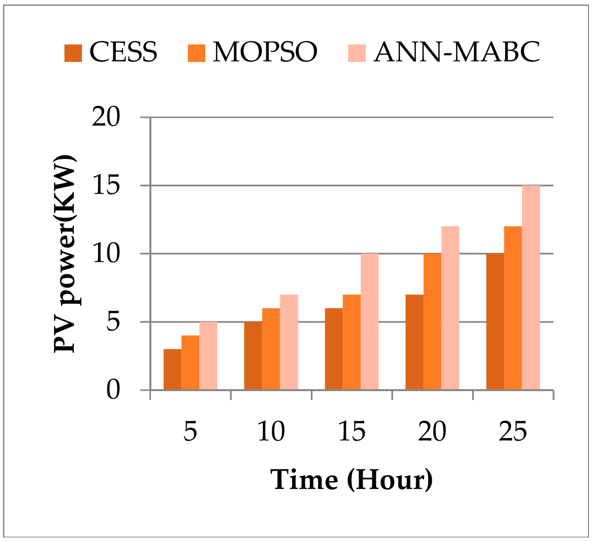

Figure 5. Comparative results of generated power using PVS.

Figure 6 displays the comparison of outcomes for wind-generated electricity. The recommended method provided the best generation schedule programming in conjunction with D/R to reduce MG's operation costs linked to client information. The MGS producing costs are thereby kept to a minimal while employing MABC. PVS, WT, ES, and MT powers are taken into account as the inputs in MABC within the minimum and maximum boundaries.

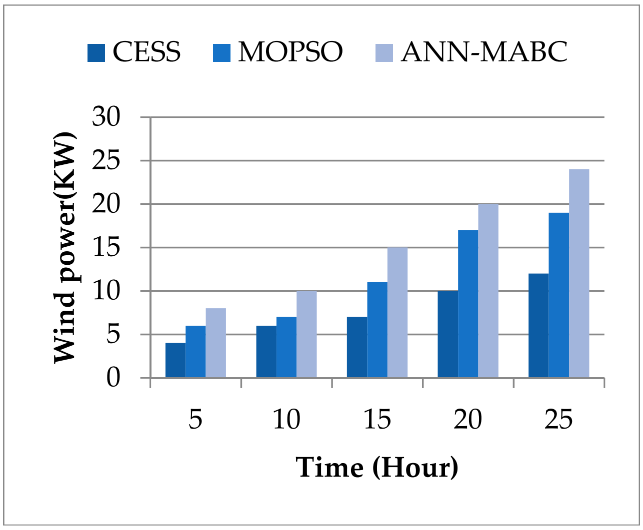

Figure 6. Comparative results of generated power using wind.

5. Conclusions

This study suggests a hybrid energy system with a power management controller that uses a hybrid MABC-based ANN for better power management and RES utilization. The suggested strategy aims to reduce manufacturing costs while also making greater use of RES. Storage systems, WT, and PVS form the foundation of the microgrid-linked system. Assessing system security, reliability, and efficiency of the suggested technique will help in overcoming the unpredictable nature of RES and uncertainty of load requirements. The value of using different PDFs to display resource data was assessed. Over time, this will enhance stochastic scheduling and power management for a reasonable production load. The effectiveness of the suggested method was evaluated once it had been put into use in the MATLAB/Simulink working environment. When compared to current techniques, such as CESS and MOPSO, the proposed strategy outperformed them. The data showed a 25% reduction in overall producing costs for each time period when D/R was properly controlled in real time. When compared to previous strategies, the suggested method required less computing time. The suggested approach of power control includes factors like customer reactions and offering priorities not included in proposed algorithms. To solve this issue, future enhancement of power controllers should (1) include factors like customer reactions and offering priorities implemented in proposed algorithms, and (2) incorporate hybrid optimization algorithms to improve reductions in overall producing costs for each time period.

Author Contributions: Formal analysis, U.R., D.T. and S.R.; Conceptualization, S.R. and E.R.; data curation, D.T.; validation, U.R.; supervision, D.T. and E.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data can be obtained from the corresponding author upon request.

Acknowledgments: We acknowledge the institutional management for their support in carrying out this work.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ahmethodzic, L.; Music, M. Comprehensive review of trends in microgrid control. *Renew. Energy Focus* **2021**, *38*, 84–96. [CrossRef]
2. Roslan, M.F.; Hannan, M.A.; Ker, P.J.; Mannan, M.; Muttaqi, K.M.; Mahlia, T.I. Microgrid control methods toward achieving sustainable energy management: A bibliometric analysis for future directions. *J. Clean. Prod.* **2022**, *348*, 131340. [CrossRef]
3. Zahraoui, Y.; Alhamrouni, I.; Mekhilef, S.; Basir Khan, M.R.; Seyedmahmoudian, M.; Stojcevski, A.; Horan, B. Energy management system in microgrids: A comprehensive review. *Sustainability* **2021**, *13*, 10492. [CrossRef]
4. Espín-Sarzosa, D.; Palma-Behnke, R.; Núñez-Mata, O. Energy management systems for microgrids: Main existing trends in centralized control architectures. *Energies* **2020**, *13*, 547. [CrossRef]
5. EI-Bidairi, K.S.; Nguyen, H.D.; Jayasinghe, S.D.G.; Mahmoud, T.S. Multiobjective intelligent energy management optimization for grid-connected microgrids. In Proceedings of the IEEE International Conference on Environment and Electrical Engineering and IEEE Industrial and Commercial Power Systems Europe, Palermo, Italy, 12–15 June 2018.
6. Naz, M.N.; Mushtaq, M.I.; Naeem, M.; Iqbal, M.; Altaf, M.W.; Haneef, M. Multicriteria decision making for resource management in renewable energy assisted microgrids. *Renew. Sust. Energ. Rev.* **2017**, *71*, 323–341. [CrossRef]
7. Kumar, A.; Sharma, S.; Verma, A. Optimal sizing and multi-energy management strategy for PV-biofuel-based off-grid systems. *IET Smart Grid* **2020**, *3*, 83–97.
8. Reddy, S.S. Optimization of renewable energy resources in hybrid energy systems. *J. Green Eng.* **2017**, *7*, 43–60. [CrossRef]
9. Kanchev, H.; Lu, D.; Colas, F.; Lazarov, V.; Francois, B. Energy management and operational planning of a microgrid with a PV-based active generator for smart grid applications. *IEEE Trans. Ind. Electron.* **2011**, *58*, 4583–4592. [CrossRef]
10. Zhou, H.; Bhattacharya, T.; Tran, D.; Siew, T.S.T.; Khambadkone, A.M. Composite energy storage system involving battery and ultracapacitor with dynamic energy management in microgrid applications. *IEEE Trans. Power Electron.* **2010**, *26*, 923–930. [CrossRef]
11. Perez, T.C. A Mini-Review of the Environmental Footprint of Lithium-Ion Batteries for Electric Vehicles. *J. Comput. Mech. Manag.* **2023**, *2*, 43–52. [CrossRef]
12. Yang, F.; Feng, X.; Li, Z. Advanced microgrid energy management system for future sustainable and resilient power grid. *IEEE Trans. Ind. Appl.* **2019**, *55*, 7251–7260. [CrossRef]
13. Molderink, A.; Bakker, V.; Bosman, M.G.; Hurink, J.L.; Smit, G. Domestic energy management methodology for optimizing efficiency in smart grids. In Proceedings of the IEEE Bucharest PowerTech, Bucharest, Romania, 28 June–2 July 2009; pp. 1–7.
14. Aghajani, G.; Ghadimi, N. Multi-objective energy management in a micro-grid. *Energy Rep.* **2018**, *4*, 218–225. [CrossRef]

15. Zhang, X.; Sharma, R.; He, Y. Optimal energy management of a rural microgrid system using multi-objective optimization. In Proceedings of the IEEE PES Innovative Smart Grid Technologies, Washington, DC, USA, 16–20 January 2012.
16. Indragandhi, V.; Logesh, R.; Subramaniyaswamy, V.; Vijayakumar, V.; Siarry, P.; Uden, L. Multi-objective optimization and energy management in renewable based AC/DC microgrid. *Comput. Electr. Eng.* **2018**, *70*, 179–198.
17. Marzband, M.; Sumper, A.; Ruiz-Álvarez, A.; Domínguez-García, J.L.; Tomoiagă, B. Experimental evaluation of a real time energy management system for stand-alone microgrids in day-ahead markets. *Appl. Energy* **2013**, *106*, 365–376. [CrossRef]
18. Pain, P.; Sadhu, A.; Das, K.; Kanjilal, M.R. Design and Implementation of Multi-Operative Reversible Gate for Even/Odd Parity Generators in Quantum Based Technologies. *J. Comput. Mech. Manag.* **2023**, *2*, 20–28. [CrossRef]
19. Surender Reddy, S.; Park, J.Y.; Jung, C.M. Optimal operation of microgrid using hybrid differential evolution and harmony search algorithm. *Front. Energy* **2016**, *10*, 355–362. [CrossRef]
20. Momoh, J.A. *Smart Grid: Fundamentals of Design and Analysis*; John Wiley & Sons: Hoboken, NJ, USA, 2012.
21. Liu, X.; Xu, W. Economic load dispatch constrained by wind power availability: A here-and-now approach. *IEEE Trans. Sustain. Energy* **2010**, *1*, 2–9. [CrossRef]
22. Karaboga, D.; Basturk, B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *J. Glob. Optim.* **2007**, *39*, 459–471. [CrossRef]
23. Punriboon, C.; So-In, C.; Aimtongkham, P.; Rujirakul, K. A Bio-Inspired Capacitated Vehicle-Routing Problem Scheme Using Artificial Bee Colony with Crossover Optimizations. *J. Internet Serv. Inf. Secur.* **2019**, *9*, 21–40.