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AN ENERGY MANAGEMENT SYSTEM USING OPTIMIZED HYBRID ARTIFICIAL NEURAL NETWORK FOR HYBRID ENERGY SYSTEM IN MICROGRID APPLICATIONS

Abdallah Qusef[1], Alaan Ghazi[2], Aras Al-Dawoodi[3], Najeh Rajeh Alsalhi[4*], Eman Ahmad Shudayfat[5], Abdellateef Alqawasmi[6], Sami Al-Qatawneh[4], Sharefa Murad[7]

[1] Princess Sumaya University for Technology, Amman, Jordan
[2] Computer Technical Engineering, Al-Qalam University, Iraq
[3] College of Computer Science and Information Technology, University of Kirkuk, Kirkuk, Iraq
[4] College of Arts, Humanities, and Social Sciences, University of Sharjah, Sharjah, U.A.E.
[5] Department of Creative media, Luminus Technical University College, Amman, JORDAN
[6] College of Education, Humanities and Social Sciences Al Ain University, Al Ain, UAE.
[7] Faculty of Information Technology, Applied Science Private University, Amman, Jordan,

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Research Paper

Abstract: *Different energy sources are typically incorporated into coordinated MGS (Micro Grid Systems) using energy management systems. It is challenging to integrate acceptable energy management models in MGS mainly due to the unpredictable nature, availability estimations and complexities in regulating RES (Renewable Energy Sources). Energy policies are encouraging incorporation of RES while reducing the usage of fossil-based fuels resulting in the need to optimize RES. This study's major goal is to lower running costs of grid-connected MGSs while predicting PV (photovoltaic) based electricity and load demands in near future. In order to enhance the performance of micro-grids, this work focuses on creating a technique for integrating optimized ANN (artificial neutral networks) into an EMS (Energy Management System). The schema called EMS-HANN (Energy Management System - Hybrid ANN) is proposed in this work and it includes forecasts, planning, data gathering, and HMI (human-machine interfaces) components. Day-ahead PV power and load demand estimates are combined with a 3-level SWT (stationary wavelet transforms) as part of the forecasting module's enhanced hybrid forecasting technique and GWO-HANN (grey wolf optimization-based Hybrid Artificial Neural Network). The scheduling module employs AEHO (Adaptive Elephant Herding Optimisation)-based scheduling to deliver the optimal power flow for grid-connected*

[*] Corresponding author: nalsalhi@sharjah.ac.ae (N. R. Alsalhi)
a.qusef@psut.edu.jo (A. Qusef), alan@alqalam.edu.iq (A. Ghazi), aras.ghazi86@uokirkuk.edu.iq (A. Al-Dawoodi), e.shudayfat@saejordan.com (E. M. Shudayfat), abdellateef.alqawasmi@aau.ac.ae (A. Alqawasmi), salqatawneh@sharjah.ac.ae(S. Al-Qatawneh), s_murad@asu.edu.jo (S. Murad)

MGS. Subsequently, DAQ and HMI modules monitor, analyse, and change forecast and schedule input variables. The proposed model for applications of MGS is implemented along with current algorithms in MATLAB/Simulink platform where outcomes demonstrate better performances of the suggested model as compared to comparable efforts.

Keywords: *MicroGrid Systems, Energy Management System (EMS-ANN), 3- Level Stationary Wavelet Transform (SWT), Grey Wolf Optimization-based Hybrid Artificial Neural Network (GWO-ANN), Adaptive Elephant Herding Optimization (AEHO).*

1. Introduction

The prevailing comprehension of power systems is undergoing a transformation due to economic and environmental motivations, alongside technical progress. The majority of the current electrical grid infrastructure in the United States was built during the 1930s (Varshney, 2022). Over the course of the past four decades, the old and overburdened electricity infrastructure has seen a total of five notable instances of power outages. Electric power plays a pivotal role in driving the economic growth of nations on a worldwide scale. Meeting the increasing energy demand for electricity poses a significant challenge due to the global population growth. Producing electric power is an arduous task that exerts significant pressure on the power market. The power-generating company has used renewable energy sources (RES) as a means to address the challenges encountered in the power industry and improve energy consumption. Microgrid systems (MGS) have emerged as a contemporary and auspicious methodology for tackling these challenges by restructuring the existing energy infrastructure and ensuring the reliability of electricity provision. Microgrid systems (MGS) refer to low-voltage distribution networks that establish a connection with distribution substations through points of common coupling (PCC). These MGS are often located downstream of the substations. Distributed generators (DGs), distributed energy storage (DES), and regulated loads are components comprising the microgrid system (MGS). When it comes to the control and operation of a grid, the unique characteristics and dynamics of a Microgrid System (MGS) present a particular difficulty. The optimal energy management strategy might vary significantly from a conventional power system, contingent upon the characteristics and prevalence of distributed energy resources (DERs) and distributed energy system (DES) nodes inside a given microgrid system (MGS) (Mohammad, Ahmed, & Kim, 2021). During instances of blackout or brownout, a typical Microgrid System (MGS) operates in two distinct modes: interconnected modes, which are connected to major grids by distribution substation transformers, and independent mode.

The MGS, or Microgrid System, comprises conventional power plants, multiple renewable energy sources (RES), energy storage facilities, and consumer demand. According to Albarakati et al. (2022) these more cost-effective systems have the potential to be situated in closer proximity to load centres compared to traditional centralised power plants because to their sustainability and compactness (Ghazi et al., 2021). The predominant share of this emerging trend is constituted by wind and solar energy systems. The exclusive focus on the development of solar and wind power generating systems has been well regarded. The management and regulation of reactive power play a critical and essential role in power systems. The challenges associated with implementing a renewable-based power grid system mostly emerge from the electrical demand and meteorological factors upon which the energy source relies (Pires, Pires, & Cordeiro, 2023). Power grid systems employ demand response strategies, commonly referred to as demand response energy resources (RES), in order to mitigate energy usage. The distribution component of this system introduces additional challenges related to design and selection of power inverters. The problem has been resolved through the application of a model that determines the suitable allocation of the renewable energy system. Certain devices are well-suited to operate in conjunction with renewable energy-generating systems when the appropriate load utility is employed. This improves performances of cellular, battery, converter circuit, and capacitor (Aqilah et al., 2023).

The utilisation of non-traditional energy sources such as solar and wind energy is expected to be the most feasible and probable approach for fulfilling the global energy demands in the future (Albaker, Alturki, Abbassi, & Alqunun, 2022). Reactive power management utilising machine learning techniques is employed in the radial distribution system to mitigate power losses and predict wind speed. The application of hybrid renewable energy systems (RES) in conjunction with machine learning techniques is employed to identify optimal solutions for the management of power systems. The integration of renewable energy sources (RES) with the power grid necessitates the implementation of many control systems in order to optimise power flows across buses. The management of the MGS's power is a critical and intricate factor to take into account when utilising RES (Hado et al., 2022). While it may appear more straightforward to categorise the strategies as centralised and distributed power management, distinguishing between the two can provide a challenge. The decentralised control approach, also known as the structure of several local controllers operating under a single global supervisory controller, stands in contrast to the master/slave strategy that necessitates a high data bandwidth link. The decision-making process is commonly employed as a means to distinguish between centralised and dispersed control (Al-Dawoodi et al., 2019; Zebra, van der Windt, Nhumaio, & Faaij, 2021). In essence, a centralised technique refers to a decision-making approach where power distribution determinations are exclusively determined by a single component, whether it be tangible controllers or virtual agents. This stands in contrast to the decentralised nature of decision-making across the Multi-Grid System (MGS). The majority of contemporary MGS (multi-agent system) initiatives exhibit hierarchical architectures including central controllers, alongside a number of decentralised efforts employing MAS (multi-agent system) approaches. The negotiation process among agents plays a crucial role in the operational mechanism of Multi-Agent Systems (MAS) (Gonal & Sheshadri, 2021), which is fundamentally different from the conventional control mode that has been investigated. Negotiation can be utilised to achieve power equilibrium and promote economic optimisation.

Nevertheless, the incorporation of diverse energy sources to address the increasing load demand presents novel challenges in power management and control. Consequently, the primary issue at hand pertains to the provision of cost-effective electricity to consumers, taking into account optimisation strategies (Ramos & Costa-Castelló, 2022). In order to ensure continuous and cost-effective fulfilment of load demand, it is imperative to effectively manage the scheduling of available power supplies. Emergency Medical Services (EMS) can fulfil significant functions inside grid-connected Microgrid Systems (MGS) by effectively managing energy-producing resources and storage systems, hence leading to financial benefits. The aforementioned system possesses the capability to regulate power distribution and transmit signals to the key control units of the MGS, hence facilitating the attainment of predetermined objectives. The aim of this study is to integrate artificial neural networks (ANN) into energy management systems (EMS) in order to improve the performance of microgrids (MGS).

The major goal of the research is to reduce the overall operating costs of grid-connected MGS while also projecting PV electricity and load demand in the near future. The remainder of the research is organised as follows; part 2 examines the sophisticated techniques used in MGS's power management procedure. Section 3 outlines the methodology's recommended approach. The findings and discussion are presented in section 4. Section 5 covers the conclusion and further research.

2. Literature Review

In this section reviews the some of the recent techniques for the power management using artificial intelligence in hybrid energy for micro grid applications.

Chandrasekaran, Selvaraj, Amaladoss, and Veerapan (2021) enhanced the smart grid model by incorporating RES and implementing an improved optimal variation technique. The primary contribution of this research article is in the creation of a novel smart grid framework that utilises renewable energy sources and incorporates artificial neural networks (ANNs) to effectively regulate voltage levels and ensure optimal reactive power distribution within grid networks. The abovementioned objectives are accomplished through the utilisation of DSTATCOM, which integrates renewable energy sources (such as solar and wind energy) with artificial neural networks (ANN) to enhance power control efficiency. The fulfilment of energy requirements can be achieved through the reception of necessary energy inputs from solar and wind-based Microgeneration Systems (MGSs). Feed Forward Neural Networks (FFNN) can also be employed for the control of Multi-Generator Systems (MGSs), with the aim of optimising power generation by considering voltage profiles and minimising power losses. The utilisation of Distribution Static Compensator (DSTATCOM) in Microgrid Systems (MGS) aids in the regulation of reactive power levels within permissible thresholds, hence improving voltage profiles and reducing power losses.

The utilisation of ACO (Ant Colony Optimisation) algorithms has been observed in the context of AEDG (Advanced Energy Design Guide) MGS (Modelica-based Generic Supervisory) frameworks, specifically for the purpose of implementing intelligent supervisory controls. This approach was initially introduced by Colson et al., as cited in the work of Tepe and Irmak (2022), where it was referred to as dispatch controls. The use of Ant Colony Optimisation (ACO) was employed for the purpose of power management in Microgrids (MGS), taking into account many factors such as environmental limitations and multifaceted aims, the availability of fuel/resources, and economic considerations. The study introduced the use of the constraint satisfaction problem (CSP) technique as a means to address the challenges posed by intricate multi-objectives and multi-constraints in energy management for integrated Advanced Energy Design Guide (AEDG) systems.

Although developing MGS power management control is a difficult task, it is essential for the widespread adoption of AEDG systems. A MGS-DERs was presented by Juma, Mwinyiwiwa, Msigwa, and Mushi (2021) for a rural isolated system made from a solar PV system, both a WT-PMSG (wind turbine connected to synchronous permanent magnet generator) and a BESS (battery energy storage system) were utilised. MPPT (Maximum power point tracking) PI (Proportional integral) controllers were used in the study to regulate DERs for obtaining MPPT (maximum power tracking) and error corrections. MPPTs use P&O (perturb and observe) methods and track maximum power points in DERs. PI increments are based on Ziegler-Nichols technique. The study's simulations on MATLAB/Simulink for continuous and steploads showed that controllers allowed BESS to charge despite load fluctuations and other external factors including wind speeds and irradiances. The DC MGS output voltage closely matched the reference which are applicable for far away grids.

The authors Arkovi et al., as mentioned in the work of Kontogiannis, Bargiotas, and Daskalopulu (2021), put forward the concept of fuzzy expert systems for the purpose of controlling demands, managing renewable energy sources (RES) and electrical energy storage in microgrid systems (MGS) and smart homes. These systems aim to automate the management of storages, regulated loads, and energy, hence enhancing overall energy management efficiency. The fuzzy expert system is utilised to optimise the storage and utilisation of energy, with the aim of maximising the financial gains derived from renewable energy sources (RES). The fuzzy expert system utilises input factors such as insolation, electrical energy costs, temperatures, wind speeds, and unpredictable power demands to facilitate energy management. Grid measurements can directly give these inputs, or alternatively, data forecasting algorithms can be employed to obtain them. This work proposes a series of expert system rules, provides output defuzzification, and applies fuzzification to input variables as a means to regulate energy production and consumption.

In order to ascertain the amount of energy generated, the loads under control, and individual consumption, three distinct outputs have been designated. In order to improve the performance of MGS (Multi-Generation Systems), Aguila-Leon, Vargas-Salgado, Chiñas-Palacios, and Díaz-Bello (2022) developed a methodology that involves the integration of optimised artificial networks into a self-adaptable energy management system. Artificial neural networks (ANNs) were sequentially connected in the model described. The PSO (Particle Swarm Optimisation) approach is utilised to optimise each Artificial Neural Network (ANN) in the proposed model. The objective of this model is to estimate and provide data to the energy management system. The model in the MATLAB/Simulink environment is supplied with experimental data. In order to validate the proposed model, a correlation analysis is conducted to examine the relationships between system variables across different artificial neural networks (ANNs).

The analysis of the system's response is conducted by evaluating the root mean squared error and performing linear regression. This analysis is carried out following the simulation of tests that are designed based on experimental data. To achieve optimal performance and cost-effectiveness in electrical frameworks, Roy et al. quoted in Sami et al. (2021) proposed a hybrid strategy that incorporates the utilisation of renewable energy sources (RES). The hybrid approach is generated by combining the bacterial foraging optimisation algorithm (BFOA) with artificial neural network (ANN) techniques. In this particular context, the term "MGS" encompasses photovoltaic systems, wind turbines (WTs), and energy storage devices. The recommended strategy for implementing controls involves the regulation of power flows between grids and energy sources. In order to comprehensively analyse the effectiveness of demand response (DR) programmes, it is imperative to take into account many factors such as customer reactions, offer priorities, demand sizes, durations, and the resulting reduction in cost of energy (COEs). The proposed method was implemented and evaluated on the MATLAB/Simulink platform, and its performance was compared to that of established methods, namely the genetic algorithm (GA) and artificial bee colony (ABC) algorithms. According to the research findings, the suggested maximum outputs for photovoltaic systems (PV), wind turbines (WT), microturbines (MT), and batteries were 7.5 kW, 9 kW, 15.5 kW, and 4.5 kW, correspondingly.

In their study, Jirdehi, Shaterabadi, Tabar, and Jordehi (2022) presented a new modelling approach, based on the work of Moghaddas-Tafreshi et al., that aims to optimise the management of electrical and thermal energy in multiple carriers MGS. The proposed strategy also takes into account system limits in order to minimise operation costs.The experimental setup encompassed a diverse array of power generation devices, including fuel cells, waste-to-energy facilities, wind turbines, and boilers, among others.The MGS comprised several components, namely a boiler, an anaerobic reactor-reformer system, a microturbine, a fuel cell, a garbage-burning power plant, a wind turbine creation system, an inverter, a rectifier, and other energy storage units. The model utilises day-ahead forecasting (24 hours) to predict the electrical and thermal demands of an MGS network. The estimation of wind turbine power generation is similarly predicated on a one-day forecast. A Monte Carlo simulation is employed for the purpose of assessing the thermal loads, electrical demands, and wind power generation due to the inherent instability of day-ahead forecasts. The allocation of non-essential loads is determined by the real-time pricing demand responses. The utilisation of the particle swarm optimisation technique has been observed to result in a reduction of operational expenses within micro-grid systems.

According to Kumar, Rizwan, and Nangia (2022), a hybrid MGS is created by combining accessible RES with interactions with modern power networks.

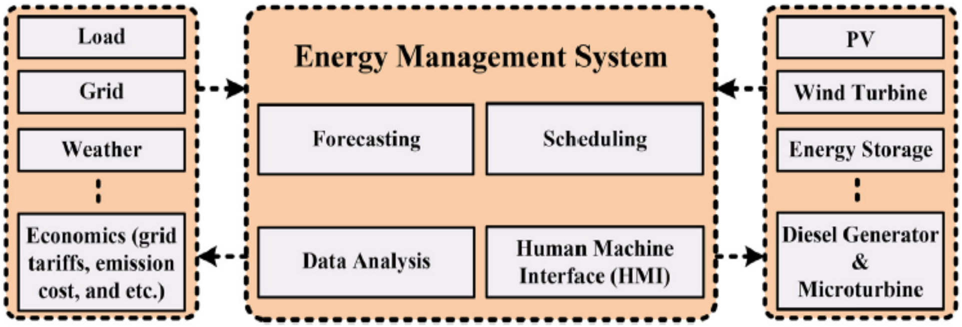
The proposed approach entails the utilisation of a hybrid system that combines a wind energy conversion system with solar photovoltaic technology, hence resulting in an integrated microgrid solution. The proposed approach integrates renewable energy sources (RES) with a meta-heuristic optimisation method to achieve optimal energy distribution in a grid-connected hybrid microgrid system (MGS). The primary purpose of the recommended method is to select the optimal size for a renewable energy-based microgrid system (MGS) based on the load profile and time of usage. A comparison analysis was conducted using case study data and additional sources to authenticate this methodology. The study observed notable cost reductions of 30.88% and 49.99% of the rolling cost when comparing mixed integer linear programming-in EMS and fuzzy logic based EMS, respectively.

Boujoudar, Azeroual, Elmoussaoui, and Lamhamdi (2021) developed an intelligent control technique for a microgrid system (MGS) consisting of grid-connected solar panels, lithium-ion battery energy storage units, and photovoltaic panels. The energy management system employs an intelligent controller for the bidirectional DC/DC converter (BDDC) to facilitate the process of charging and discharging batteries. The major innovation of this approach is in the utilisation of Artificial Neural Networks (ANN) for bidirectional converter control and the computation of battery State of Charge (SOC). The performance and robustness of the proposed control technique were elucidated through MATLAB/Simulink simulations.

In their seminal work, Kim, Oh, and Choi (2022) proposed an innovative methodology for achieving cost-effective energy management. Their strategy incorporates the analysis of power outputs and consumptions, leveraging auxiliary Internet of Things (IoT) devices. The study successfully verified the accuracy and effectiveness of analytical and energy management models using real-world datasets obtained from operational CMGs.

The implementation of a comprehensive management strategy (CMG) can result in a decrease of 2.16% in daily electricity prices and a reduction of 3% in peak power use, as compared to scenarios without CMG. In their study, Sami et al. (2021) employed a hybrid strategy to optimise the programming of an electrical framework. This technique aimed to achieve a balance between reducing manufacturing costs and enhancing the utilisation of renewable energy sources (RES). The researchers used the Bacterial Foraging Optimisation Algorithm (BFOA) and the Hybrid Artificial Neural Network (HANN) to optimise the storage of Microgrid Systems (MGS) in relation to wind and photovoltaic (PV) technologies. The suggested control system involved the monitoring of power flows between grids and renewable energy sources (RES). It took into account several factors such as demand responses (DR), customer reactions, offer priority, DR sizes, durations, and minimal cost of energies (COEs). The researchers applied their methodology on the MATLAB/Simulink platform and compared the results with alternative approaches such as the genetic algorithm (GA) and artificial bee colony (ABC) algorithms.

3. Proposed Methodology



4. *Figure 1. Proposed Energy Management system*

This work suggests using EMS-HANN in grid-connected MGS in order to enhance performances in terms of reduced running costs while also forecasting PV powers and load demands in the near future. EMS-HANN includes four main components namely forecasts, schedules, DAQ, and HMI. The forecasting module uses updated hybrid forecasts encompassing 3-level SWTs and GWO-ANN (grey wolf optimization-based ANN) for PV power productions and predicting load demands. The scheduling module uses AEHO to ensure that grid-connected MGS receives best power flows. The DAQ and HMI module are used to monitor, assess, and make changes to inputs of forecast and schedule modules. The general procedures of the recommended technique are shown in Figure 1.

3.3.1. Proposed EMS

This paper proposes intelligent EMS for grid-connected MGS based on better hybrid predictions and optimum schedules (see Fig. 2). The proposed EMS meets load demands by acquiring information regarding load demands, weather characteristics, and other factors. PV powers and processing historical data are inputs for predicting best suitable load demands, PV powers; and energy resources schedules. Additionally, DAQ and HMI modules enable users to assess and keep track of input elements including historical weather data, PV powers, and load demands. In the sections that follow, this work's proposed modules are discussed in details.

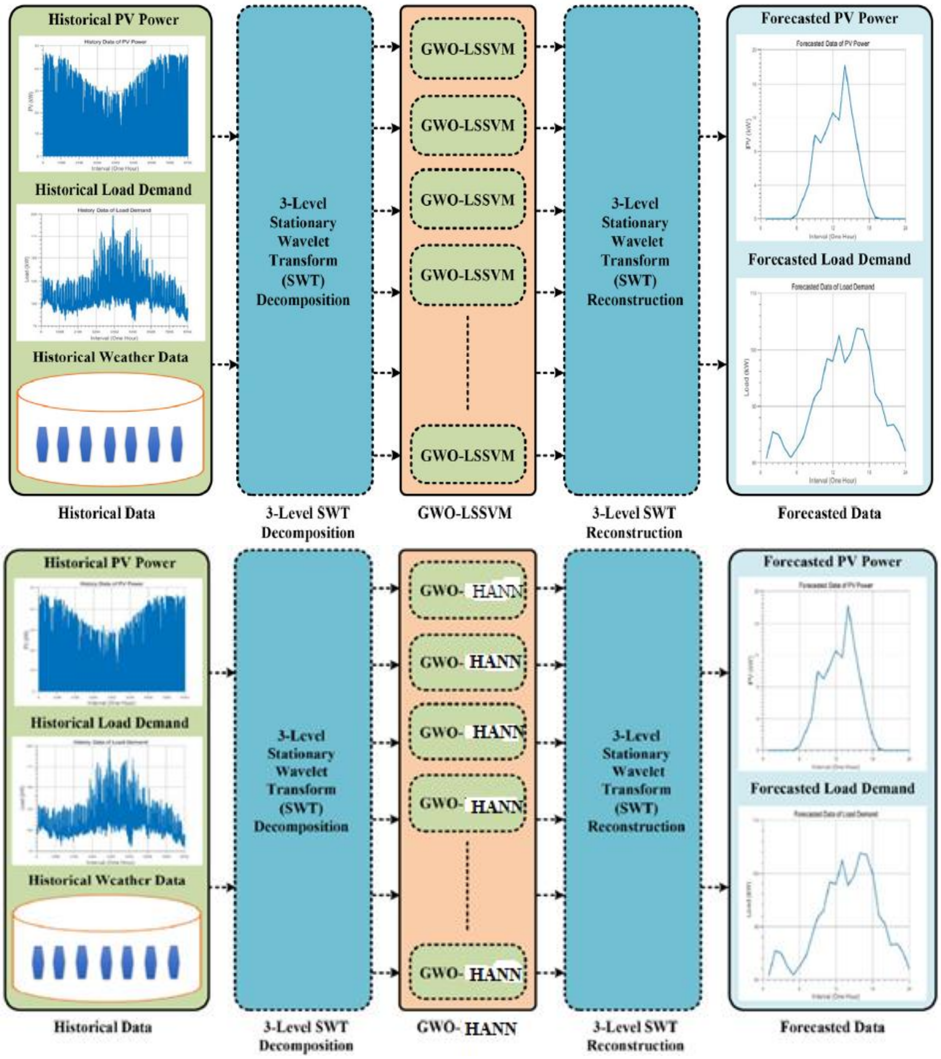


Figure 2. Proposed EMS-HANN system

3.3.2. Hybrid forecasts using GWO-LSSVM based on Wavelet transforms

As seen in Fig. 2, a hybrid forecasting technique based on three levels of SWT, GWO, and HANN is proposed using 3-level SWT on historical data from meteorology. PV powers and load demands were split into low and high frequencies and results were fed as inputs to GWO-HANN for forecasts of PV powers and load demands. GWO-HANN outputs were then reconstructed using 3-level SWTs where day's expected PV powers and load demands were estimated. Forecasting accuracy of this work's suggested method was enhanced by appropriate weather-linked parameters which influence PV power outputs and load demands. The relationships between these two parameters and weather were investigated in this work using Pearson correlation coefficients. The proposed approach demonstrated that climate which frequently influences PV power generations and loads,is significantly affected by temperature and humidity. Hence, correlations of temperature and humidity were also considered in this work.

3.3.3. SWT

SWT was used to divide historical meteorological data (PV powers and load demands). SWT's capacity to isolate sub-components via filtering eventually helped it surpass original climates, load demands, and PV power data, boosting forecasting accuracy for both PV powers and load demands. SWTs addressed the shift invariance difficulties of DWTs (discrete wavelet transforms) by incorporating up-sampling and eliminating down-sampling in the filter coefficients. SWT, like DWT, properly splits incoming signals into high and low-frequency components. SWT, on the other hand, provides output signals that are not decimated. Sparks and changes in input signals were shown using details, while broad patterns were shown using approximations. Using high- and low-pass filters, the input data was separated into approximations and details for the multilevel decomposition.

The applications of SWTs in load demand forecasts proved their utility in this work. Historical data (PV power, load demand, and meteorological conditions) were evaluated using 3-level SWTs. The selections of MWF (mother wavelet function) was as it impacted 3-level SWT functions significantly by the inclusions of Coiflet (coif), Daubechies (db), and Symlet (sym). Wavelet forecasts were based on Daubechies type MWF of order 4 (db4) as it was demonstrated by Rana et al. demonstrated that db4 was the most appropriate and effective MWF for predictions.

3.3.4. GWO

GWO is a swarm-based heuristic technique inspired by social structures and instincts of grey wolf hunts for prey. Social orders of grey wolves are divided into four groups as seen in Fig. 3. Leaders make up the first level ("alpha") of the social hierarchy. They include both male and female greywolves who make decisions about things like hunting, where to sleep, when to wake up, etc (Seyyedabbasi & Kiani, 2021). The second level is made up of "beta" wolves who aid the alphas in making choices and carrying out plans on the lower categories. The third-level "delta" wolves are dedicated to carrying out the aforementioned commands and supervising the omega group. At the bottom of the hierarchy are the "omega" wolves, who are in charge of obeying the instructions of the aforementioned groups and carrying out the job of hunting. The remaining responses are regarded as an omega in the search space in GWO, whereas the top three best solutions are assumed to be alpha, beta, and delta. Grey wolves surround their preys during hunting, which may be stated mathematically using Equations (1) and (2), respectively:

$$F = \left|G.X_{prey}(t) - X(t)\right| \qquad (1)$$

$$X(t+1) = X_{prey}(t) - D.F \qquad (2)$$

where X_{prey} implies positions of preys, X stands for grey wolf's positions, t represents current iterations, and D, G are coefficients expressed in Eqs. (3) and (4):

$$D = 2a.r_1 - a \qquad (3)$$

$$D = 2.r_2 \qquad (4)$$

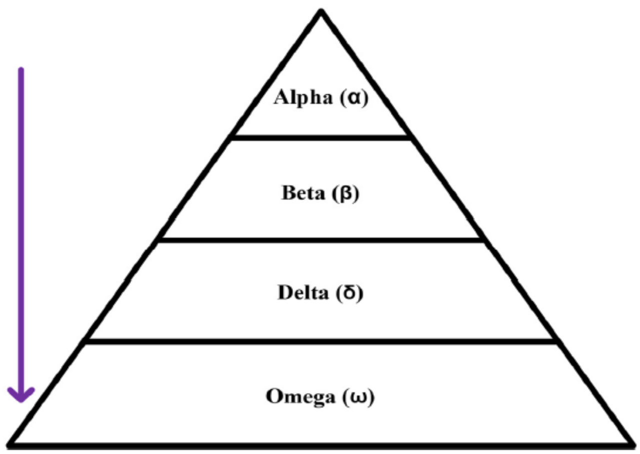


Figure 3. Social hierarchy of grey wolves.

r1 and r2 imply random integers in the range [0,1], and components a reduce linearly from 2 to 0 in iterations. The best of first three parameters are used in optimisations. The placements of other wolf groups (such as omega) are then adjusted based on these and represented mathematically as:

$$F_\alpha = |G_1 X_\alpha(t) - X(t)| \qquad (5)$$

$$F_\beta = |G_2 X_\beta(t) - X(t)| \qquad (6)$$

$$F_\delta = |G_3 X_\delta(t) - X(t)| \qquad (7)$$

Positions of preys are computed based on alpha, beta, and delta group positions using the following equations:

$$X_1 = |X_\alpha - D_1.F_\alpha| \qquad (8)$$

$$X_2 = |X_\beta - D_2.F_\beta| \qquad (9)$$

$$X_3 = |X_\delta - D_3.F_\delta| \qquad (10)$$

$$X(t+1) = \frac{X_1+X_2+X_3}{3} \qquad (11)$$

where X_α, X_β, and X_δ represent alpha, beta, and delta groups' positions, accordingly. D determines explorations/ exploitations of grey wolf searches. When compared to other competitive algorithms, GWO performs better due to effective utilisations of D. GWO devotes half of iterations to explorations and the balance for exploitations, avoiding local minima, greater explorations/exploitationsin parallel.

3.3.4.1.GWO based Hybrid ANN

Electrical technology is using artificial intelligence more and more as a result of a better knowledge of the interactions between various formulation and process factors. Fuzzy logic and neural networks (Chimmiri & Jujjavarapu, 2021) are two quickly developing technologies that might be used in the development and processing of medicinal goods. For successful prediction and formulation condition optimisation, evolutionary algorithms are used with ANN.

First-order logic and neural networks may naturally be connected by fuzzy logic, and fuzzy-neural systems appear to have flourished probably more than other forms of symbolic connectionism. Fuzzy input layers (fuzzification), hidden layers with fuzzy rules, and final fuzzy output layers (defuzzifications) are all components of three-layer feed-forward networks known as fuzzy neural networks. Layer-to-layer connections that are fuzzy in nature contain fuzzy sets, although five-layer networks containing sets in the second and fourth levels are exceptional. If there is enough input, a rule in the hidden layer will be activated. The input membership functions of the fuzzy rules are represented in the input layer. The relative weights across the layers determine membership in each fuzzy set. which may be changed using specific training procedures, much as in a typical neural network. Typically continuous, transfer functions transmit real values to the output layer of the network where they are converted to degrees of membership in fuzzy sets based on the firing of fuzzy rules in the hidden layer.

FFNNs using BP (Back Propagation) least mean-square learning methods are the most proliferated. Figure 5 depicts its topology. Network edges connect neural processing units, and neuronal inputs are assigned weights based on locations within cell's hierarchy. Net functions addinputs of neuronsfor net values which are weighted linear combinations of inputs. A hierarchical criteria in multicriteria analyses offer overall evaluations of patterns. This hierarchy encoded by hierarchical neural network with neurons representing criteria might be employed. Input neurons in networks are emphasised differently. Hidden neurons and output satisfy complex criteria and used as net functions of neurons or evaluation functions. When the criteria are considered independently, they can be merged linearly.

But in actuality, there is some correlation between the criteria. The link between the criteria cannot be captured by the linear evaluation function. The SBP (Standard BP) algorithm is proposed to address this flaw. The FBP (Fuzzy BP) method is proposed in this study as a fuzzy extension. It does not assume that the criteria are independent because it computes the net value with an LR-type fuzzy number. Another advantage of the FBP algorithm is that it never reaches a local minimum and proceeds continuously to the goal value without oscillations. Thus, the conditions for FBP convergence in network singular outputs with single- and multiple-training patterns are both necessary and sufficient.

3.3.4.2. FBP algorithm

Many neuro-fuzzy models have recently been presented for computing net values by aggregating the neuron inputs. Sugeno's fuzzy integrals are based on psychological backgrounds and can be represented mathematically as:

Step1: Random generations of initial weights w for hidden layer inputs, where $w_{ji} = (w_{mji}, w_{\alpha ji}, w_{\beta ji})$are LR type fuzzy numbers and generate weight sets w' for hidden output layers

Where $w'_{kj} = (w'_{mkj}, w'_{\alpha kj}, w'_{\beta kj})$

$$w_{ji} = (w_{mji}, w_{\alpha ji}, w_{\beta ji})$$

$$w'_{kj} = (w'_{mkj}, w'_{\alpha kj}, w'_{\beta kj})$$

Step2: Let (I_p, D_p) $p = 1, 20 \ldots N$ input/output patterns needed for training by fuzzy BP where $I_p = (I_{p0}, I_{p1}, I_{p1})$and I_{pi}stand for LR-type fuzzy numbers.

Step3: Assign values for α and η; Alpha=0.1 Neta =0.9

Step4: Get next pattern set (I_p, D_p) Assign ($O_{pi} = I_{pi}$, i=1,2,3..1

Step5: Compute the input to hidden neurons

$$O'_{pj} = f\left(NET_{pj}\right), j = 1,2 \ldots., m; O'_{p0} = 1$$

Where $NET_{pj} = CE\ (\sum W_{ji} O_{pi})$

Step6: compute the hidden to output neurons

$$O''_{pk} = f\ (NET'_{pk})\ , k = 1,2, \ldots n;$$

Where $NET'_{pk} = CE\ (\sum W_{ji} O'_{pj})$

Step7: compute change of weights Δ w'(t) for the hidden output layer as follows

Compute

$$\Delta E_p(t) = (\partial E_p / \partial w'_{mkj}\ , \partial E_p / \partial w\alpha kj, \partial Ep / \partial w'_{\beta kj})$$

Compute

$$\Delta w'(t)\ =\ -\eta \Delta E_p(t) + \alpha \Delta w'(t-1)$$

The update weight i of hidden to output neuron is

$$W'(t)\ = W'(t-1)\ + \Delta W'(t)$$

Step 8: Compute change of the weights Δ w'(t) for the input hidden layer as follows

Let

$$\delta_{pmk} = -\left(D_{pk} - O''_{pk}\right) O''_{pk} (1 - O''_{pk}).1$$

$$\delta_{pmk} = -\left(D_{pk} - O''_{pk}\right) O''_{pk} \left(1 - O''_{pk}\right).\left(-\frac{1}{3}\right)$$

$$\delta_{pmk} = -\left(D_{pk} - O''_{pk}\right) O''_{pk} \left(1 - O''_{pk}\right).\left(\frac{1}{3}\right)$$

Compute

$$\Delta E_p(t) = (\partial E_p / \partial w'_{mji}\ , \partial E_p / \partial w\alpha_{ji}, \partial Ep / \partial w'_{\beta ji})$$

Compute

$$\Delta w'(t)\ =\ -\eta \Delta E_p(t) + \alpha \Delta w'(t-1)$$

Step 9: update weight for the input-hidden-output layer as

$$W(t)\ = W(t-1)\ + \Delta W(t)$$

$$W'(t)\ = W'(t-1)\ + \Delta W'(t)$$

$\boldsymbol{Step}$ **10**: $p = p + 1;$

if (p<=N) go to step 5

Step 11: COUNT_of_ITRNS=COUNT_OF_ITRNS+1;

if COUNT_of_ITRNS<ITRNS

{

Reset pointer of first pattern in the training set;

P=1;

Go to step 5;

}

Step12: output w' and w'' the final weight sets.

3.3.5. Scheduling using AEHO.

Scheduling is important to EMS since it assist in regulating electricity flows between utility grids and MGS. MGS functions economically by taking into account the several options. In this paper, we suggested an objective function to lower the operational costs of MGS, which can be described as follows:

$$Of = min \sum P_{PV}(t)C_{pv} + P_{BC}(t)C_{BESS} + P_{BD}(t)\,C_{BESS} + P_{G-1}(t)C_{G-1} \rightarrow t \in [1{:}m] \quad (12)$$

where C_{G-1} stands for electricity prices of drawn powers from main grids; C_{pv} represent maintenance costs for PV P_{BC} and C_{BESS} the maintanence costs for BESS, P_{BD} ; and m is total time conssumed. The primary decision variables in the grid-connected MGS are PV power P_PV, BESS charge and discharge power, imported electricity from grid P_(G-1), BESS capacity B_C, and binary decision variable (). Numerous technical restrictions, such as power balancing and BESS constraints, should be considered in order to reduce the operating cost of grid-connected MGS. The charging power, discharging power, and capacity restrictions for BESS are among them. These technological restrictions can be formally described using the following equations:

$$\sum P_{Load}(t) - P_{PV}(t) + P_{BC}(t) - P_{BD}(t) - P_{G-1}(t) = 0 \rightarrow t \in [1{:}m] \quad (13)$$

$$B_C(t) = B_C(t-1) + \frac{24\eta_{BC}}{m} P_{BC}(t) + \frac{24\eta_{BD}}{m} P_{BD}(t) \rightarrow t \in [1{:}m] \quad (14)$$

$$P_{BD}(t) - P_{BD}^{max}\alpha \leq 0 \rightarrow t \in [1{:}m] \quad (15)$$

$$P_{BC}(t) + P_{BC}^{max}\alpha \leq P_{BC}^{max} \rightarrow t \in [1{:}m] \quad (16)$$

There are several optimization variables bounds that need to be considered for solving the optimization problem, and these bounds are listed below:

$$P_{PV}^{min} \leq P_{PV}(t) \leq \mathrm{P}_{\mathrm{PV}}^{\mathrm{max}} \rightarrow \mathrm{t} \in [1{:}\mathrm{m}] \quad (17)$$

$$B_c(0) = B_{initial} \quad (18)$$

$$B_{initial} = B_{end} \quad (19)$$

where a are binary decision variables for BESS; hBC and hBD are efficiencies of BESS while charging and discharging, and BCap is the capacity of BESS.

. In this research, an AEHO was used to conduct optimum scheduling in grid-connected MGS.

- **AEHO**

As shown below, the proposed EHO (Elephant herding optimisation) technique (Wang, Deb, & Coelho, 2015) is a novel metaheuristic nature-inspired optimisation method that discovers the ideal solution to advance multicast routing:

1) CLAN OPERATOR

The elephants are divided into clans, each of which is led by a matriarch. As a result, each elephant's future position in clan ci is determined by matriarch ci. It is possible to update the elephant j in clan ci, as shown in Equation 1:

$$x_{new,ci,j} = x_{ci,j} + \alpha \times (x_{best,ci} - x_{ci,j}) \times r \qquad (20)$$

where$x_{new,ci,j}$ stands for newly updated elephant j's position in clan ci and $x_{ci,j}$ its old position. α ∈ [0, 1] are scales that determine matriarch ci's influences $x_{ci,j}$. $x_{best,ci}$ represents matriarch ci, the fittest elephant individual in clan ci and r ∈ [0, 1]. Fittest elephants in clan cans are updated as:

$$x_{new,ci,j} = \beta \times (x_{center,ci}) \qquad (21)$$

where 1 ≤ d ≤ D indicates dth dimensions, and D stands for total dimensions. nci represents clan's elephant counts ci. $x_{ci,j}$, d implies dth individual elephant $x_{ci,j}$. The clan ci's center, $x_{center,ci}$ is computed using Equation 21 and using D.

4. Results and Discussion

The proposed EMS-HANN system's numerical findings (forecasting and scheduling) are evaluate for effectiveness and efficiency where forecasting and scheduling are carried out for various conditions with randomly selected days in four seasons.

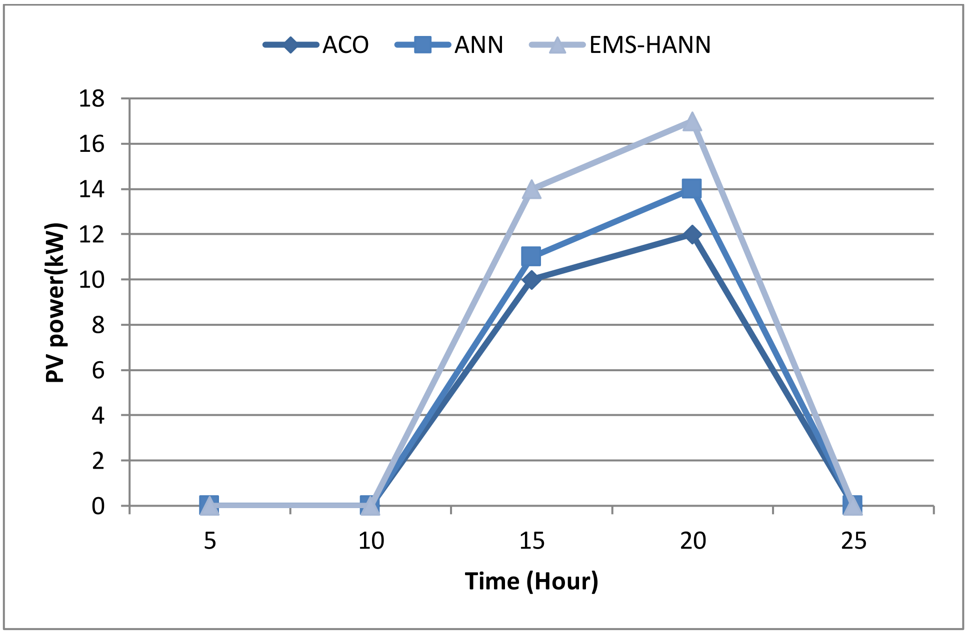


Figure 4. Comparison results of PV power (kW) between proposed and existing methods

Figure 4 depicts the results of PV powers and load demands future predictions for selected days. On the y-axis of each graphic is the power in kilowatts, and x-axis represents time in hours. PV power forecast outputs using the recommended technique and those of the ACO and CNN. However, the result cognate with the findings of Tayab et al. (2021) on energy management system for microgrids, employing the weighted salp swarm algorithm and a hybrid forecasting technique to address the issue of variable output caused by the intermittent nature of renewable energy resources. This variability leads to an imbalance between power generation and demand inside microgrids. The Energy Storage System (ESS) is employed to achieve equilibrium between electricity generation and consumption. In the context of microgrids (MG), the presence of multiple renewable energy resources and energy storage systems (ESS) necessitates the implementation of an energy management system (EMS). This EMS is capable of effectively managing the stochastic characteristics of renewable energy resources, as well as scheduling the power output of these resources and ESS. However, the EMS is efficient in managing the power flow between the MG resources and the main grid while ensuring cost-effective operation.

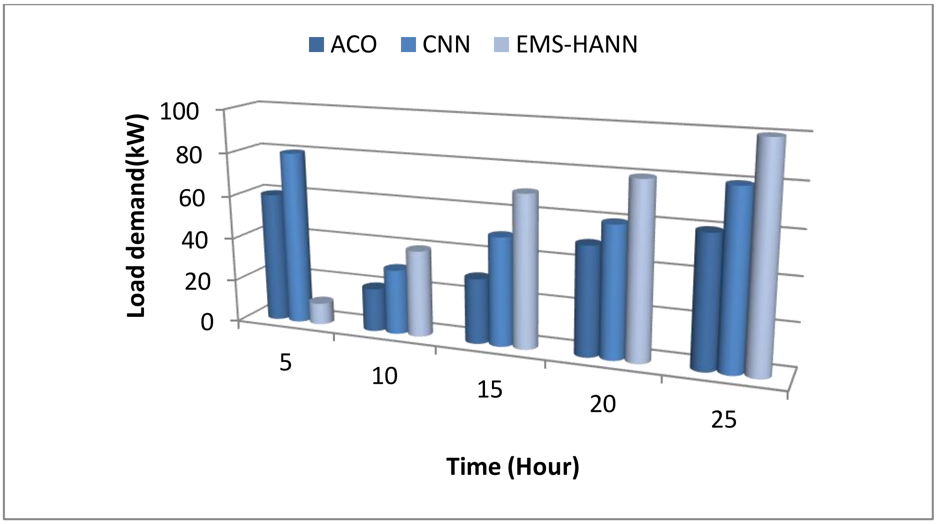


Figure 5. Comparison results of load demand between the proposed and existing methods

The study of the system's load requirement using both modern and traditional methods is shown in Figure 5. Additionally, the suggested method's maximum generated and used powers are studied and contrasted with those of the existing techniques. The graphics demonstrate how the suggested method forecasts load demand more accurately than current methods. The effectiveness of the novel method is assessed by comparing its fitness graphs, computation times, and overall generation costs with existing approaches. Supporting the result of Shufian and Mohammad (2022) revealed in their study that the intermittent characteristics of renewable energy resources, as well as the load and market pricing, as noteworthy creative considerations in the context of MG. In the traditional heuristic approach, data is subject to forecasting with a degree of uncertainty rather than being known with absolute precision. One potential approach for enhancing the operational efficiency of microgrids is through the utilisation of optimization-based techniques to enhance the development of energy storage systems and energy management systems (EMS). And that the EMS plays a crucial role in the integration of distributed energy resources in the microgrid systems, particularly in when power generation, transmission, distribution, utilisation, and variable pricing are involved.

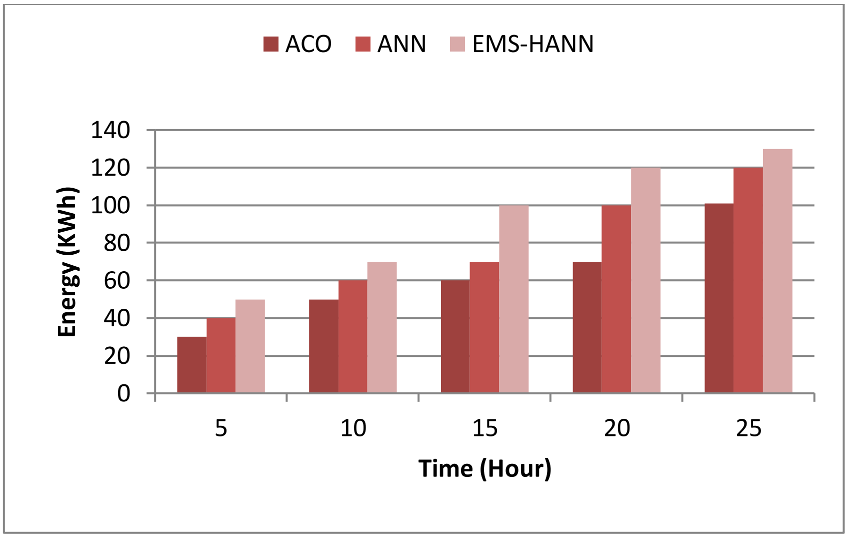


Figure 6. comparison results of energy

Figure 6 depicts the results of the energy comparison between the suggested and existing techniques. It illustrates the BECC's capacity during the course of a 24-hour summer day. As illustrated in Fig. 6, both optimal scheduling theories predict that the BESS will charge and discharge during off-peak and peak hours, respectively. Because of the AEHO, the BESS may charge at full capacity for the first six hours of the day and discharge at around half capacity during peak hours. BESS begins charging after peak hours and eventually reaches its initial capacity limit. This findings was in agreement with the work of Wang, Deb, and Coelho (2015) who posit that the non-linear attributes of a Battery Energy Storage System (BESS) might lead to discrepancies in the stored energy between the planned operation and the actual operation. The energy held in a Battery Energy Storage System (BESS) exhibits a non-linear relationship with the charging/discharging power. This relationship is determined using the Special Ordered Set of the Type 2 (SOS2) approach. The unit commitment (UC) problem in a microgrid context incorporated the application of BESS-operation models that provide constant power conditioning system (PCS) input/output power efficiency. The Battery Energy Storage System (BESS) demonstrated a similar operational performance to the real-world scenario when compared to the conventional model, resulting in a reduction in the margin of error during the energy charging and discharging process. As a result, the SOS2 system was rendered economically viable through the implementation of measures aimed at minimising the expenses associated with mistake correction and mitigating the likelihood of straying from the designated operational parameters of the Battery Energy Storage System (BESS). In addition, the SOS2 algorithm demonstrates effective resolution of operational challenges arising from the nonlinearity inherent in Battery Energy Storage Systems (BESS).

5. Conclusion

The energy crisis, the degeneration of the current power grid, and the emission issues compel people to investigate the area of smart grids, in which MGS with integrated renewable resources play an important role. As a result, having a well-planned and managed power management system is critical. In this study, the goal is to reduce the overall operating expenses of grid-connected MGS as well as short-term projections of PV electricity and load demand. Forecasts, schedules, DAQ, and HMI are all part of EMS-HANN. The forecasting module provides an enhanced hybrid forecasting technique that combines a 3-level SWT and GWO-HANN. PV power and load needs may be forecasted in advance. The scheduling module employs AEHO scheduling to ensure that grid-connected MGS receives the maximum amount of power flow. The forecasting and scheduling modules' input variables are then monitored, assessed, and modified using the DAQ and HMI modules. The quantity of energy transmitted between the MGS and the main grid to charge PHEVs grows as RER/DER generation rises, in accordance with the findings of offline digital time-domain simulations and software verification. The results show that the suggested power management technique works better than previously reported solutions.

6. Implications of the Study

The following implication of findings are proffer for the study of optimized hybrid artificial neural network (ANN) for managing energy in microgrid applications

- It leads to increased energy self-sufficiency, reducing dependency on the main grid and promoting energy resilience during outages.
- It optimizes energy generation and distribution, minimizing costs and environmental impact while ensuring a stable power supply.
- This technology supports the integration of renewable energy sources, contributing to a greener energy landscape.
- The use of an optimized hybrid ANN in microgrid energy management signifies a significant step towards sustainable and resilient energy systems, with far-reaching implications for a cleaner and more reliable energy future.

7. Limitations of the Study

This study has encountered certain limitations worth acknowledging including:

1. The accuracy of the HANN model heavily depends on the quality and quantity of data available for training. Inadequate or noisy data also led to suboptimal performance.
2. The computational complexity of the HANN poses challenges for real-time implementation, particularly in resource-constrained environments.
3. The generalisability of the HANN across different microgrid scenarios and system configurations requires further fine-tuning for diverse applications.
4. The cost of implementing a sophisticated EMS using HANN is prohibitive for smaller scale microgrids.

8. Future Research Directions

Future research directions in the field of energy management systems (EMS) for hybrid energy systems in microgrid applications hold significant promise for advancing renewable energy integration and grid sustainability. One emerging avenue of exploration is the utilization of optimized hybrid artificial neural networks (ANNs) to enhance EMS performance.

Firstly, future research should focus on developing more sophisticated ANN architectures tailored specifically for microgrid applications. These ANNs should incorporate deep learning techniques, reinforcement learning, and advanced optimization algorithms to improve prediction accuracy and decision-making within the EMS.

Secondly, the integration of real-time data from Internet of Things (IoT) devices and advanced sensors can further enhance EMS capabilities. This can lead to more accurate forecasting of renewable energy generation, load demand, and storage capacity, enabling finer-grained control of energy flows within microgrids.

Thirdly, exploring the potential of decentralized EMS algorithms that enable microgrids to autonomously exchange surplus energy with neighboring grids or adapt to dynamic changes in energy supply and demand is crucial. This can improve grid resilience and facilitate peer-to-peer energy trading.

Lastly, sustainability and environmental impact assessments should be integrated into EMS design, ensuring that future systems consider not only economic but also ecological factors.

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