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Energy-Optimized Intelligent Distributed Energy Resources in a Microgrid

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Abstract The modern smart grid replaces old power networks with networked microgrids with a high penetration rate of energy-storing technology and renewable energy sources. The control strategy is one of the most crucial elements in operating a microgrid power system. Although different control methods have been examined to control hybrid microgrids with interlinking converters, further research is required. A distributed energy system is built on integrating battery energy storage systems (BESS) and renewable energy sources like wind, solar and small hydro systems. The charging facilities for electric cars are also included in this scheme. This work proposed a novel Zebra-based Deep Belief Neural Mechanism (ZbDBNM) with a robust control mechanism. Using a Zebra-based fitness function, this novel approach predicts and optimizes energy cost, Total Harmonic distortion (THD) and power loss to match established norms. An evaluation of the proposed control approach's effectiveness and efficiency against established techniques is provided through comparison.

Keywords Microgrid, renewable energy resources, Total Harmonic Distortion, Cost of Energy, Zebra optimization.

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1. Introduction

The Collaboration for Electric Reliable Technologies defines the term microgrid as the combination of demands and supplies that function as a unified system to provide electricity and heat [1]. Microgrids are applied in several contexts. Campus microgrids, which enable central management and guarantee connectivity even when cut out of the primary power supply, are frequently installed in educational institutions [2], jails, and military facilities [3]. Microgrids such as islands or isolated locations have been established where connecting to the network are impractical [4]. More distributed energy resources (DER) are getting put on-site as commercial microgrids are built [5]. DERs are renewable sources of Energy which are usually found where electricity is needed, at the consumer's location [6]. They are made up of regulated loads, systems for storage, and compact, modular generators. Electricity sources may include non-dispatchable or transportable units [7]. Because they are dependent on the environment, non-dispatchable electrical power sources have an irregular nature and fluctuation in production [8]. A facility may reach its peak demand when an inconsistent source needs a better electricity supply. By holding electricity and providing it later, energy storage devices can help lessen the disparity in demand and supply of energy [9]. Manageable loads are thermally and electrical requirements that can be lowered or modified at crucial points, as well as those whose demands can be planned within a range of operating parameters that have been predetermined [10].

Controlled loads modify their power usage in response to a control signal triggered by a price signal or a power supply disruption [11]. Energy is a crucial component of humanity's existence and growth, as it affects national

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economies, individual means of subsistence, and a country's ability to compete strategically [12, 13]. Coal, natural gas, and oil are classic fossil-fuel-based energy supplies that have seen significant consumption in the past few years due to the steep rise in global energy needs [14]. As a consequence, global environmental and Energy crises have become more and more prominent, impeding economic growth and having a significant effect on the way people live. In particular, it was established that the combustion of energy sources like petroleum and coal releases greenhouse gasses, including dioxide from combustion [15], which are the primary causes of worldwide warming and other climate-related issues. In this instance, the growth and application of green Energy is currently the sole means to ensure socially sustainable growth regarding energy issues due to the older conventional electrical organizations and the growing demand from consumers for reliable electricity [16].

Many nations are taking action to increase energy consumption efficiency and aggressively promote Energy from renewable sources to achieve sustainable energy use [17, 18]. Early dispersed generating technology directly impacted how the grid operated, altering every branch of electricity flow's one-sided flow properties and creating challenges for the system's preservation and management [19, 20]. A small degree of distributed generating access won't significantly impact the transmission system. The adverse effects of distributed energy accessibility on electrical network suffering, power flow, harmonious, voltage light up, current shorts, thermal endurance, dynamic reliability, and transient reliability are more pronounced when the grid's porosity increases.

The following sums up the research's main contributions:

- During the initial phase, a distributed system will be created integrating BESS and renewable energy sources like solar, wind, and small hydropower into the grid system.
- Also included in this system are an electric car and its charging stations.
- Consequently, a novel ZbDBNM with a sufficient control mechanism has been designed.
- Henceforth, the power loss and THD are predicted and optimized to the desired level based on the zebra fitness.
- Subsequently, the proposed control approach is compared with various existing models, which will prove the efficiency of the proposed methods.

The work was provided as relevant information and problems in the second section. The solution to the problem is then covered in more detail in the third section. Section four looks at the creative solution's validation outcome. The research project's conclusion was presented in section five.

2. Related Works

Recent works as literature related to this research work are described as follows.

Latif et al. [21], in this paper, a unique two-level proportional-integration plus double derivative PI (1 + DD) control was designed for improving the dynamic oscillations of microgrid comprised of various new clean energy resources. Research is being done using hybrid plug-in electric cars, nonsensitive heated water heaters, and renewable energy sources such as wind, tidal, and biodiesel. First, a two-level PI (1 + DD) gadget concept has been applied to distributed microgrid power systems based on renewable energy sources. A system aims to control the power contribution of different subsystems into the nonsensitive load under different scenarios to improve system dynamics.

Azab et al. [22] three evolutionary optimization strategies were used in this paper to tune their fractional-order (FO) -PI controllers put in place in a DAB-based DC microgrid. Determining the ideal stability of voltage values for these controllers is the aim. First, offline optimization used dual dynamic bridge-based (DAB) small-signal designs. Following the determination of each set of ideal variables, a frequency-domain model for analysis was created using the passivity-based criterion to forecast the DC microgrids constant voltage. The microgrid regulators using the obtained two sets of settings for each algorithm satisfy a Nyquist criterion, and thus, stable responses are to be anticipated.

Vasilakis et al. [23] review covers the various organizational structures used for Microgrids (MG) supervision, namely the first, second, and third ones, and a systematic categorization of every technique used, including centralized, distributed, and decentralized models. It also compares and contrasts the key characteristics of the practical implementations of the various methods. Analyzing the physical attributes of each MG, the presented results demonstrate that successful uses at all stages of MG management can be more tailored. The findings indicate that the primary level involves achieving effective frequency, voltage, and stability of the MG along with proper power allocation among DER; the secondary level involves providing optimal economic management and restoring the voltage and rate outings to nominal values; and the downstream network's surrounding MG interactions are effectively managed.

Aljafari et al. [24] this work proposes A hybrid AC and DC microgrid with different control approaches to get the highest power level in solar power plants and FC. Based on the leads obtained through numerous control methods, which include the Maximum power point tracking (MPPT) method, the particle swarm optimization (PSO) algorithm, fuzzy logic controller (FLC), and artificial neural network (ANN) increases the time taken to settle of the proposed combination DC microgrid. FLC has a higher efficiency rating than other control methods. The results reveal that the fuzzy MPPT prediction hybrid microgrid electrical output method is exact, effective, and reliable. The grid and standalone systems were both used in this investigation. It is likely to choose a specific MPPT method in different applications as the outcome of this examination into various ways of managing MPPT devices.

Ferahtia et al. [25] an optimized energy management strategy (EMS) constructed around SSA is proposed in this paper for a photovoltaic array (PV), fuel cell (FC), and a battery DC microgrid. The proposed EMS controls the sharing of authority in the DC microgrid using an optimization process. Moreover, the system's power model and the EMS's complete design are provided. An evaluation is conducted between the PSO-based EMS and the planned SSA-based EMS. According to the simulation results, the SSA-based EMS offers remarkable power quality and safe operation, while the proposed EMS offers better power management and performance. The local generators can meet the loads with this suggested approach. The suggested EMS is tested under a range of operational scenarios, and while considering the power system's physical limitations, it achieves its predefined goals.

El Bourakadi et al. [1] the innovative, intelligent system for energy management in micro-grids with grid-connected mode, which is mostly based on wind energy, is presented in this study. The model's foundation is a deep recurrent with long short-term memory (RLSTM), which receives wind speed data as input and outputs the amount of wind power generated over the next hour. According to experimental findings, the prediction model based on long short-term memory produces accurate and excellent outcomes, but it requires higher computational resources and training time.

Al Hadi et al. [2] the suggested models utilized an Artificial neural network with an adaptive neuro-fuzzy inference system (ANN-ANFIS). A wind turbine-powered Double-Fed Induction Generator and solar photovoltaic panels are used in the first renewable generator to produce harmonics. In contrast, a wind turbine-powered Permanent Magnet Synchronous Generator and solar panels are utilized in the second. These generators build training and testing datasets for the forecasting models by generating voltage and current waveforms from real-world data. The models perform best but limit the generalizability of the models to other grid-connected renewable sources.

Zhang et al. [3] have developed a distributed control system based on multiagent reinforcement learning (MRL). It maintains privacy while implementing decentralized execution to satisfy regionally specific energy needs. To speed up learning, an attention mechanism is introduced to the centralized critic. The best Power dispatching between energy resources and the main grid is determined by the higher layer's model predictive control, and simulations demonstrate the efficacy of the suggested control strategy but do not minimize the power loss due to transmission and distribution.

Wang et al. [4] to predict multi-energy loads, a multi-task Multiple-Decoder Transformer (MDT) is employed. The model uses a consistent encoder for input data and numerous decoders for each prediction. To achieve varying degrees of attention to the encoder's output representation, each task includes its decoders for subtask learning. The model outperforms competing models in terms of forecasting accuracy and generalization capacity but fails to analyze the THD.

Kumar et al. [5] The developed novel method improves grid stability, efficiency, and load forecast accuracy by combining the Deep Dilated Attention Residual Convolutional Network with Flying Foxes (ADRCNF) PV, energy storage, wind turbines, and load demand are all components of the microgrid system. Effective load estimation and system regulation are achieved via the Flying Fox approach. It produces superior results and an astounding 98% efficiency rate. The limitation is it does not address power losses and THD, which are critical, factors affecting microgrid efficiency.

Formulas	Abbreviation
P_s	power generated by Solar Energy
P_w	power generated by wind sources
P_{hy}	power generated by the small hydro systems
T_p	total Power generated
P_l	Power loss
X_{DC}	Combined Power
T_s	cumulative stored Energy
B_{es_i}	energy stored in each battery
E_{ev_j}	energy stored in each vehicle
η_{ch_i}	BESS charging effectiveness
η_{ch_j}	EVs charging effectiveness
P_{pq}	power quality
E_s	Various sources Energy
C_s	Energy source control parameter
N_s	Storage units
ΔP_d	Change in power distribution
D_s	Energy source distribution factors
T_d	power distribution time-related parameters
N_d	number of distribution points
O_{pt}	Optimization variables
f	Fitness function
$\log_{10}$	logarithmic function
P_l	energy lost
C_e	cost of Energy
H	harmonic order
I	Current
V	Voltage
P_{Output}	actual Power
P_{Loss}	power loss
P_{Total}	total Power
P_n	power consumption
T_t	total demand
t	Time
C_n	Energy resource contribution factor

2.1. Problem Statement

Nowadays, the controller is effectively implemented to control power generation from renewable resources. However, overall control management for the grid-connected power system is limited due to the un-uniqueness power distribution. It may cause high harmonic current and power loss, which results in less power stability. So, the present research article has introduced a control management technique based on optimization and deep networks.

High harmonic current, power loss and unstable Power are some issues. Power cost is high if these problems use more Energy than the energy management system requires. Several optimal algorithms were presented in digital and mathematical forms to choose the best DG system. Determining the ideal location for DG in both balanced and unbalanced situations may lessen such problems. This work aims to use an intelligent optimal DG power system, which is prompted by these challenges and this demand.

3. Proposed Methodology

The primary intent of this work is to manage the energy resources of the DG system by optimizing power usage. Hence, a novel Zebra-based Deep Belief Neural Mechanism (ZbDBNM) control system was implemented for the DG power system. The designed architecture is defined in Figure 2. For creating the DG system, the components such as solar, small hydro, and wind have been taken, and then to apply load, the electric vehicle (EV) has been considered in this study. Also, the Battery Energy Storage System (BESS) was designed for the energy storage device. Here, the power utilization is minimized by reducing the power loss and Total Harmonic Distortion (THD). The proposed architecture is exposed in fig.1.

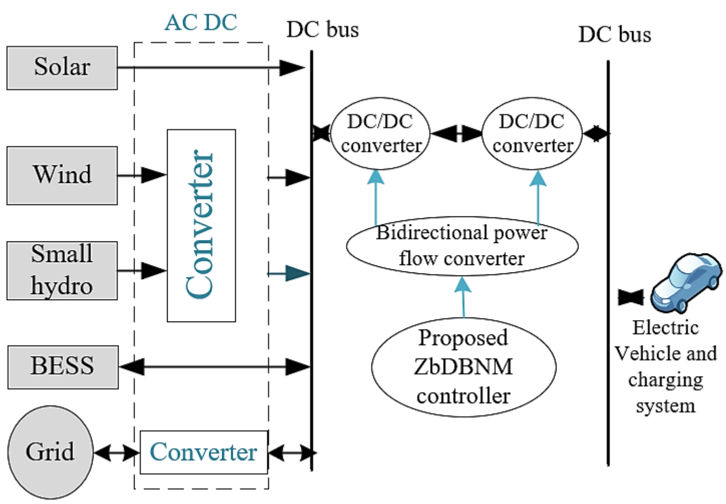

Figure 1. Proposed architecture

The Zebra best solution method was initiated to find the best location for EV when the DG was first developed for bus systems. Finally, previous related research using various performance indicators is used to validate the innovative solution's resilience.

The layered diagram for the proposed architecture is shown in Fig. 2. The ZbDBNM has an input layer, a hidden layer, and an output layer. The model starts with an input layer that gathers and processes these varied energy parameters. It has layers, where three Restricted Boltzmann Machine (RBM) are the hidden layers that are used for hierarchical feature learning. RBM 1 has 256 neurons that employ the sigmoid activation function, RBM 2 has 128 neurons with ReLU activation, and RBM 3 has 64 neurons employing Leaky ReLU activation. The Zebra Optimization Layer is incorporated to optimize power loss and THD by applying a Zebra Fitness Function in the hidden layer and dense layer for better parameter tuning. In the output layer, power loss and THD are predicted using a linear activation function. The model is optimized with a batch size of 64, an adaptive learning rate of 0.001, and a dropout rate of 0.2 for regularization across 200 epochs.

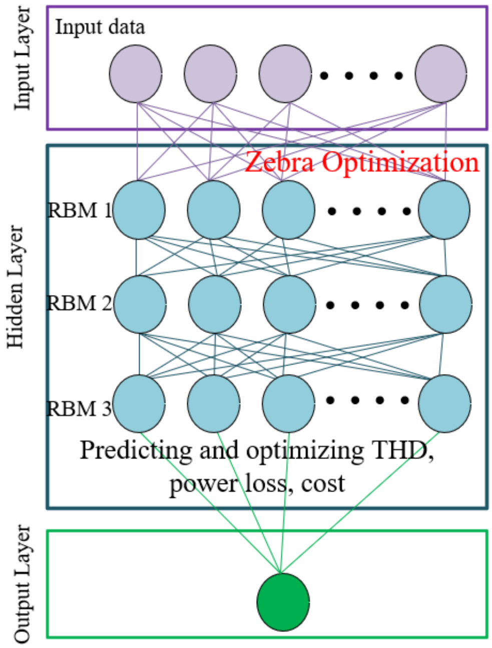

Figure 2. ZbDBNM layer

3.1. *Establishment of renewable resources with the grid*

Integrating renewable energy sources such as wind, solar and small hydro systems into the current electrical grid infrastructure is known as grid integration. Solar panels use the photovoltaic effect to directly turn sunlight into Power. Through the use of solar energy, they produce electricity. Wind turbines produce electricity by harnessing the motionless Power of the wind. A generator is powered by the turbine's rotating blades, which generate Energy. These systems turn turbines to produce Energy by using flowing water, such as rivers or streams. They use the Energy that the following water provides. Adding these renewable energy sources to the grid increases energy mix diversity and produces Power using sustainable resources. In contrast to fossil fuels, which have a limited supply and are linked to environmental problems like pollution and climate change, renewable energy sources replenish naturally and generate clean Energy without releasing greenhouse emissions.

$$X_{DC} = \sum P_s + P_w + P_{hy} \cdot (T_p - P_l) \tag{1}$$

The establishment of a DC microgrid can be expressed in Eqn. (1). Where X_{DC} is the total combined Power contributed to the grid by solar, wind and hydro P_s represents solar energy sources generate the Power, P_w is denoted by the Power generated by wind sources, P_{hy} the Power generated by the small hydro systems, T_p the total Power generated and P_l the losses due to inefficiencies in transmission or conversions. Connecting renewable energy sources to the current system is a surefire way to boost our power supply. It opens the door for a future with cleaner energy sources by lowering our dependency on filthy fossil fuels like gas and coal. Both a healthy world and dependable electricity benefit from this.

3.2. *Incorporation of BEES*

We must integrate battery energy storage systems with electric vehicles to address energy intermittency and advance clean transportation while maximizing the potential of renewable energy sources. Energy Storage with Battery When renewable energy sources produce more Energy than is immediately needed, systems are employed to store the excess. For later usage, these devices store this excess Energy. BESS holds extra Energy from renewable sources so it can be used later when demand exceeds supply or when renewable Power is less abundant. Including electric cars and the places to charge them is a calculated step in the direction of environmentally friendly transportation. These vehicles may be charged at designated stations using the electricity stored in their batteries.

$$T_s = \sum_{i=1}^{n} B_{es_i} \times \eta_{ch_i} + \sum_{j=1}^{m} E_{ev_j} \times \eta_{ch_j} \tag{2}$$

The incorporation of BESS and EVs into the system can be shown in Eqn. (2). Where T_s represents the cumulative stored Energy within the system from both BESS and EVs, B_{es_i} denotes the Energy stored in each battery energy storage system i, E_{ev_j} denotes the Energy stored in each vehicle, η_{ch_i} and η_{ch_j} are the charging effectiveness of BESS and EVs, respectively representing the effectiveness of the charging process for each system. Adding EVs to the system means extra Energy produced during off-peak hours by renewable sources or stored in BESS can be used to charge these cars. This application encourages clean transportation and maximizes the usage of renewable Energy.

3.3. Proposed ZbDBNM for power quality assessment

The innovative "Zebra-based Deep Belief Neural Mechanism (ZbDBNM)" is a power quality evaluation tool that draws inspiration from zebras' adaptability and collective intelligence. By simulating these animal characteristics, this deep learning network analyses power data at several levels and accurately detects problems like harmonic distortion and voltage instability. This new method opens the door to more efficiency and dependability in electrical systems.

$$P_{pq} = \sum_{i=1}^{n} \left(\frac{E_s \times C_s}{\sqrt{N_s}} - \frac{\Delta P_d}{\text{Max}(E_s)} \right) \times \sum_{j=0}^{1} \left(\frac{D_s \times T_d}{\sqrt{N_d}} \right) \tag{3}$$

The prediction of power quality can be expressed in Eqn. (3). Where P_{pq} represents the power quality prediction variable, E_s represents the Energy from various sources managed by the mechanism, C_s represents the control parameter associated with each energy source, N_s denotes the number of storage units managed by the mechanism, ΔP_d represents the change in power distribution across the system, D_s represents the distribution factors related to each energy sources, T_d represents the time-related parameters associated with power distribution and N_d represents the number of distribution points managed by the mechanism. A novel proposed ZbDBNM for power quality prediction integrates Zebra-inspired concepts into a deep belief neural network framework to evaluate and improve the Power in an electrical system. To validate the performance of the proposed system, the Liege Microgrid Open Data was utilized from the Kaggle site, which is collected practically (Liege Microgrid Open Data). Here, training and the data initialization process were performed using the Zebra population initialization function. In addition, the crossover ranging of data is 70% training and 30% testing. Moreover, the data was pre-processed based on the min-max scalar function with a regularization model. Then, the optimal model is implemented to optimize the THD and to attain the optimal performance.

3.4. Optimize cost, power loss and THD

The proposed ZbDBNM addresses the power system optimization problem by drawing inspiration from Zebra's well-known herd intelligence and resourcefulness. This innovative method uses deep learning networks to evaluate energy data and adjust important variables like cost, harmonic distortion, and power loss, resulting in a cleaner, more economical, and more efficient electrical grid. By emulating zebras' adaptability and optimization tendencies, the ZbDBNM opens the door to a more intelligent and sustainable power distribution industry.

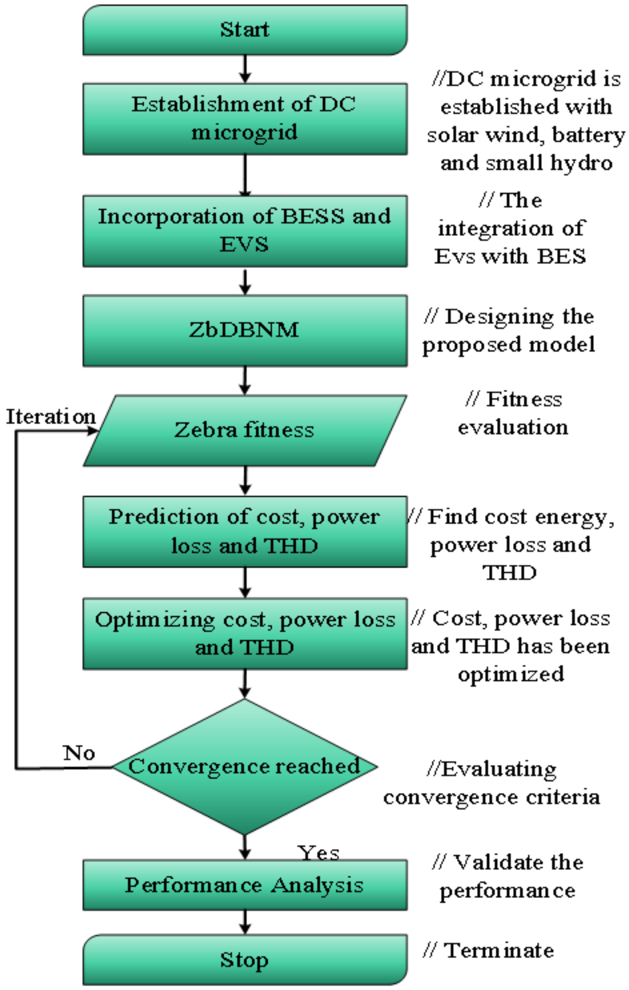

Figure 3. the Flowchart of ZbDBNM

The prime fitness function of Zebra optimization is selecting the best herd leads based on their performance. The Zebra, which helps to lead the zebra group to save grassland for the pasture, is considered as the best Zebra and optimal finding. In this present study, the cost and power loss were regulated based on the THD range. So, the desired THD range is fixed in the zebra memory; while running this algorithm, the process is repeated continuously till the desired THD is met. This process can lead to optimal power loss and energy costs. In addition, fixing the desired THD in the Zebra memory function will provide a flexibility score for the algorithm to be implemented in any power grid system profile.

$$O_{pt} = f\sum_{i=1}^{n}\frac{P_l \times C_e}{\log_{10}\sqrt{\text{THD}}} + \frac{\sqrt{P_l}}{\text{THD}} - \frac{P_l \times C_e \times \text{THD}}{100} \tag{4}$$

The cost of Energy, power loss, and THD optimization can be calculated using Eqn. (4). Where O_{pt} represents the optimization variable, f represents the fitness function of the proposed optimization, logarithmic function like $\log_{10}$ effectively compressing wide ranges of values into a more manageable scale, P_l represents the Energy lost within the system, C_e is the cost of Energy that represents the financial expense linked to energy usage. The "proposed ZbDBNM for optimizing power loss, cost of energy, and THD" is a novel technique that is processed in the dense layer of deep belief network function to improve the THD prediction and optimize it up to the desired level. Figure 3 depicts the processes carried out in the suggested model. These step processes served as the basis for the MATLAB code, and the outcomes were confirmed.

Algorithm 1: ZbDBNM

Start ()
{
  Initializing renewable energy sources()
    // Power, wind, hydro is initialized
  Establishing Power combined to the grid
  {
  int $P_s, DC, P_w, P_{hy}, T_p, P_l$
  // Initializing the DC power contribution
  X_{DC} = Power(solar energy + wind source + hydro system)
  }
  BESS Incorporation()
  {
  int $T_s, n, m, E_{ev_i}, B_{es_i}, \eta_{ch_i}, \eta_{ch_j}$
  // Initializing stored energy analysis function for each energy system in BESS and EV
  T_s = Energy stored in Battery and vehicle + BESS charging effectiveness
  }
  Power quality assessment()
  {
  int $P_{pq}, E_s, C_s, N_s, D_s, T_d, N_d$
  // Initializing the power quality prediction function
  P_{pq} = |Energy × storage units × Distribution factors|
  }
  Optimizing the power system function ()
  {
  int THD, C_e, f, O_{pt}
  // Initializing the communication parameters
  O_{pt} = (THD + cost + Power loss)
  }
}
Stop ()

4. Result and Discussion

The DC grid system and a novel suggested ZbDBNM are created and tested using the MATLAB environment on Windows 10 OS. Also, the parameters, including the cost of Energy, power loss, voltage imbalance, THD, power stability and power consumption, are calculated. The data was initialized based on the initialization process of the zebra population. Hence, the value of the zebra population size is 30; here, 30% of microgrid data is utilized for testing. Based on the testing ratio, the population count has to be changed and fixed. Then, at the level of the 100th iteration of the optimal algorithm, the desired THD range was attained; after that, the algorithm was terminated. Hence, the maximum utilized iteration is 100.

Table 1. Simulation parameters

Parameters	Description
Platform	MATLAB
Version	R2021a
Optimization	Zebra
Population	30
Iteration	100
Base MVA	1 MVA
Base kV	11 kV
Solar Irradiance	1000 W/m^2
Maximum Power	1.2 kW
Panel Temperature	25 °C
Output voltage	300 V
Wind speed	2.5 m/s
Maximum Power	2.5 kW
Cut-off speed	22 m/s
Cut-in speed	7 m/s
Output voltage	500 V
Power and X/R	20 kW and 0.7
Load	9 kW and 11.25 kVAr
β	0.01 %
Grid voltage/current	300 V / 2 A
Real Power	1.1 p.u.

Table 1 describes the simulation parameters. The parameters of a power system simulation are compiled in this table. It details the weather conditions (2.5 m/s wind speed, 1000 W/m² solar irradiance), base voltage and power levels (11 kV, 1 MVA), optimization algorithm (Zebra), and software platform (MATLAB R2021a). Next, it describes the properties of the power sources (a 2.5 kW wind turbine with a 500 V output and a cut-off speed of 22 m/s and a temperature of 250°C), the load (9 kW and 11.25 kVAr), the power factor (0.7), the grid voltage and current (300 V and 2 A), and the reactive and real Power (0.288 and 1.1 per unit, respectively). Software requirements of the proposed model are micro-grid data, simulation environment, MATLAB programming, and controlling parameters. In addition, the hardware requirements are- large micro-grid real-time or live data edge computing devices with any communication protocol that connects between server and receiver.

4.1. Case study

A revolutionary ZbDBNM was proposed to create a controlled output signal for a grid system connected to renewable resources with lower THD, energy costs, lower power loss, and improved power stability. MATLAB is utilized to simulate the proposed control architecture.

Load profiles are Three-phase reactive load, rated at 10 kVAR and type of microgrid is hybrid microgrid topology. The signals acquired using the MATLAB Simulink platform is described in Figure 4. The solar panels are powered by sunlight, which produces DC electricity. An inverter converts this DC electricity into AC that can be used in homes and businesses or sent to the grid via net metering. A battery stores extra Energy from the panels and wind turbines at night or on overcast days. When the wind blows, the turbine produces AC, which adds to the system's output. The RESE label indicates that both sources are renewable. This clean Energy can power an EV charging station, allowing you to change your electric vehicle responsibly. Showing the system's potential, the numbers 4 and 100 represent the wind turbine's power output in kilowatts and the batter's capacity in kilowatt-hours. Using clean electricity for the requirements through this integrated network of renewable energy sources and storage provides grid backup and the opportunity to participate in the electric vehicle revolution.

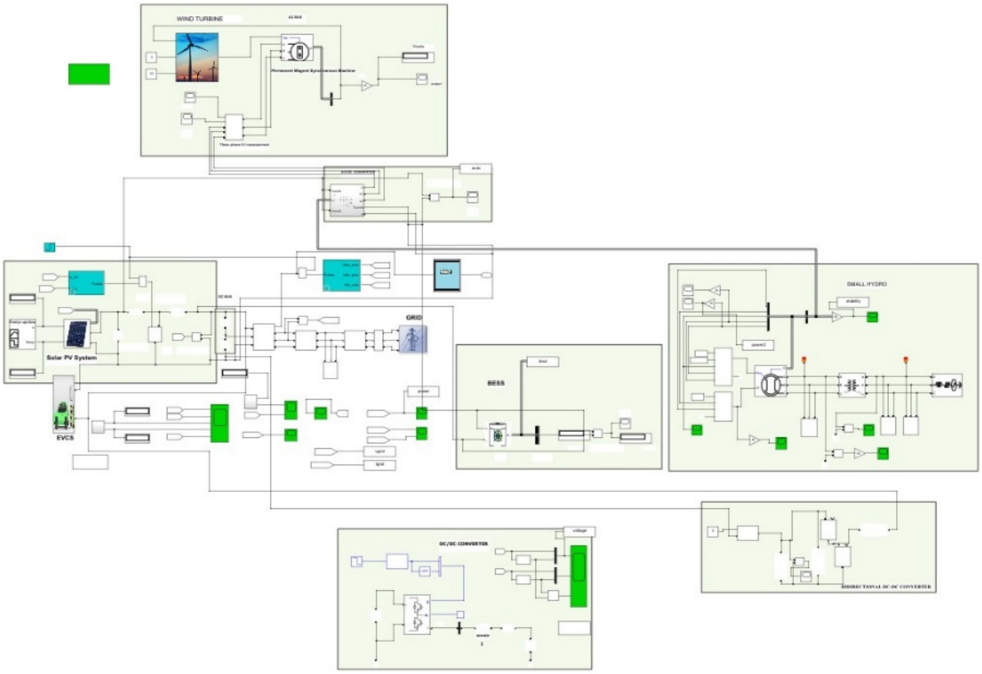

Figure 4. A simulation diagram that links a renewable energy system to the DC grid is proposed

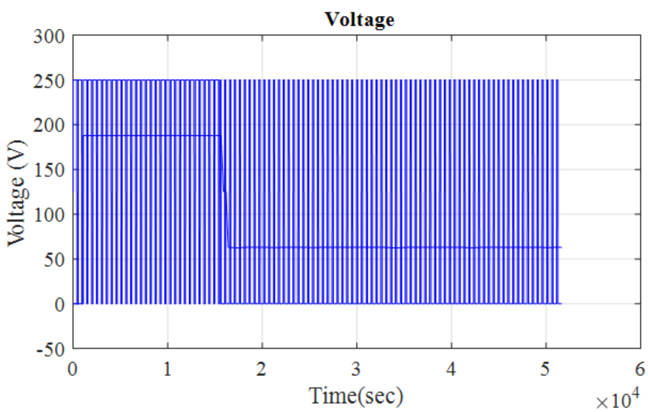

Figure 5. Voltage of the DC link

The DC link voltage is displayed in Figure 5. A second-order sigma-delta modulator receives an analogue input signal in the form of a smooth, oscillating sine wave. It then employs noise shaping and oversampling to transform the analogue signal into a digital bit stream of 1s and -1s. A 10MHz clock powers this operation, and the modulator's 1-bit quantizer converts analogue data to digital data. Out-of-band noise is eliminated using a bandpass filter with a passband of 0.1Hz to 10 KHz. The modulator, noteworthy for its transient response, shows a brief settling period of a few cycles before the result stabilities to its new value when the input signal changes rapidly.

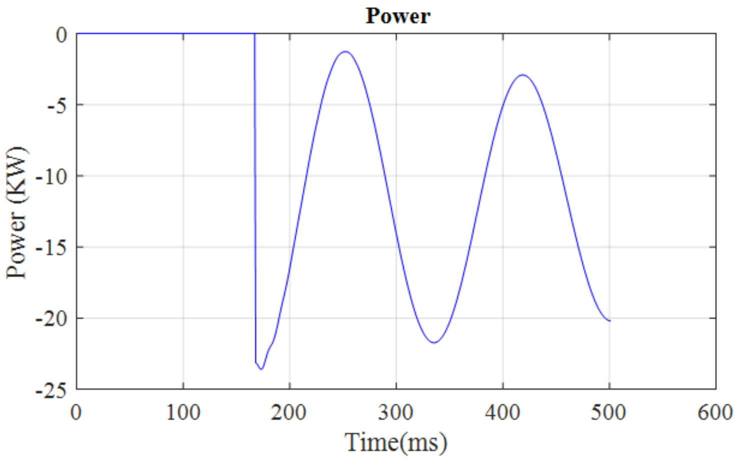

Figure 6. Provision of output electricity to the electric grid

The provision of output electricity to the electric grid is shown in Figure 6. Direct Current (DC) power is produced when sunlight strikes solar panels (PVm). After that, the DC electricity is supplied to an inverter, transforming it into alternating current (AC) electricity that buildings, businesses, or the grid may use. Excess electricity produced by the wind turbine or solar panels can be kept in the battery and used later. The term EVCE alludes to electric car charging stations, which may run on electricity produced by the system.

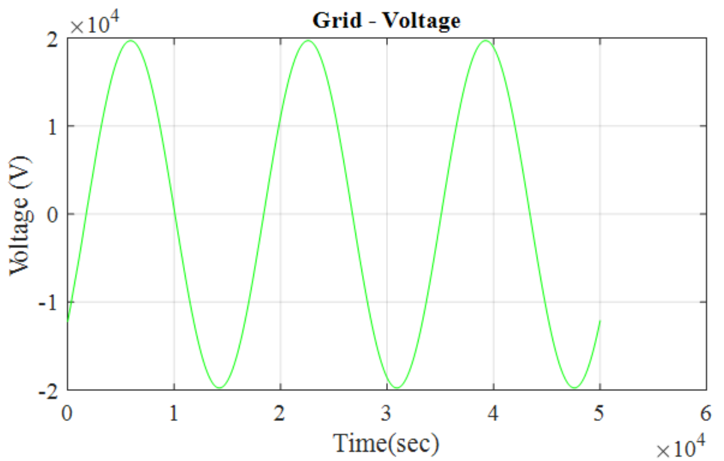

Figure 7. Effectiveness of grid voltage

The nearly constant voltage of a power grid throughout time is depicted in Figure 7, with just minor variations around a desirable level. For equipment safety and efficiency, consistency shown by a green line hugging a reference line is essential. Excessive voltage fluctuations must be avoided because of the potential for device damage or power outages. That is why a steady power source is crucial.

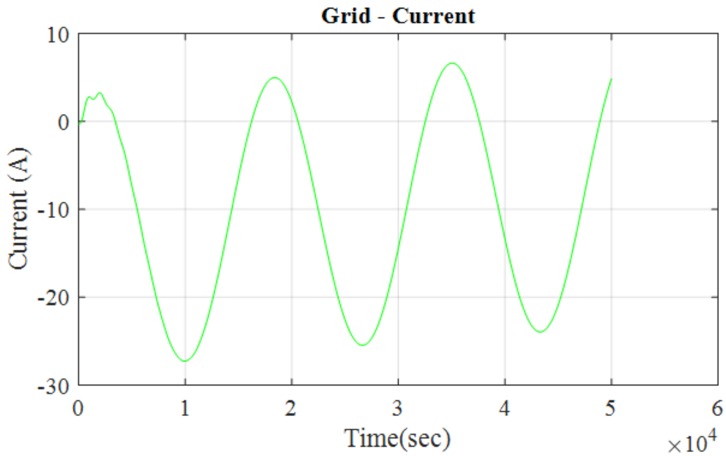

Figure 8. Effectiveness of grid current

The effectiveness of grid current is shown in Figure 8. Alternating Current (AC), frequently used in power grids, is indicated by the graph, which shows current, probably measured in amperes (A), varying over time with positive and negative values. With labels, it is easier to understand the precise numbers and the significance of the horizontal grid line, even if the X-axis most likely depicts a time in seconds. An unmarked vertical line in the centre may represent a specific time or occurrence. Additional information, such as the Y-axis's range and the vertical line's importance, would make the current variations in time and amplitude more straightforward.

The Figure 9 displays the power stability. Power stability is the capacity of the energy system to keep a steady and dependable power source. The system needs to be quick to recover from errors and shock-resistant. Stability can be restored by looking at how the system responds to changes or disturbances and ensuring it does so without any issues. This metric evaluates the microgrid system's ability to function consistently under a range of conditions, such as sudden changes in load or disruptions.

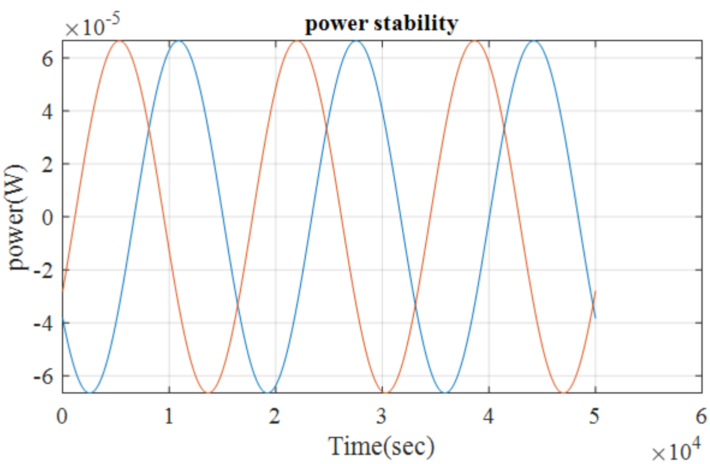

Figure 9. Power stability

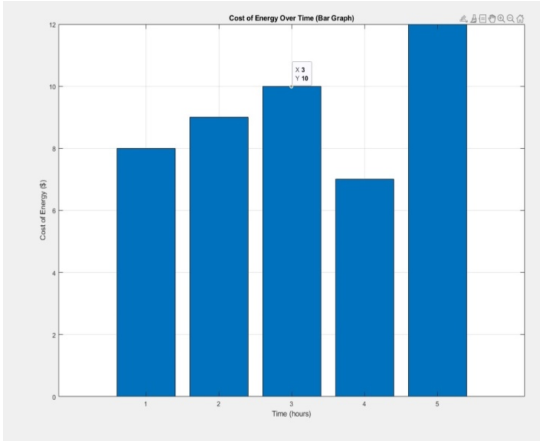

Figure 10. Cost of Energy over time

Figure 10 displays the cost of Energy and shows variations in Energy. The bottom X-axis shows the relevant time in hours, while the left Y-axis shows the cost in dollars, from $2to12$. During this period, renewable Energy has been the most economical choice, with nuclear Power coming in second. The pricing differences between energy sources are highlighted because both options are more affordable than coal and natural gas.

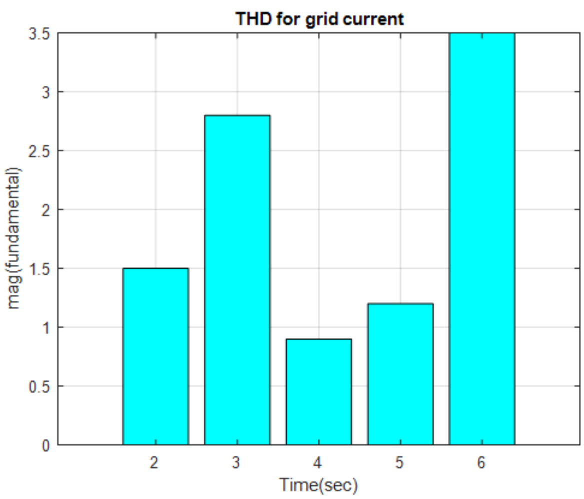

Figure 11. THD for grid current

The THD of grid current shown with time was shown in Figure 11. Although THD is continuously low, ranging from 0.5% to 1.5%, short bursts at 2 and 4 seconds indicate higher harmonic content in the waveform, suggesting transient distortions in the sinusoidality of the grid current.

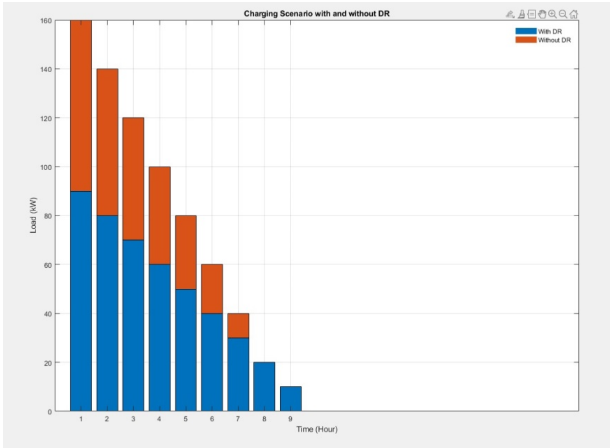

Figure 12. Load changes with and without DR

The Figure 12 shows the load changes. The y-axis on the graph represents kilowatts (kW), and the x-axis shows the amount of time in hours the electricity is consumed over a day. The scenario without demand response (DR) is represented by the blue line, which begins at 140 kW at 5 AM and progressively decreases to 100 kW by 8 AM. It stays constant until 4 PM and increases to 140 kW by 8 PM. As an illustration of the scenario with DR, the green line, on the other hand, begins at 120 kW at 5 AM, tapers down to 80 kW by 8 AM, and stays at that level until 4 PM, at which point it increases to 120 kW by 8 PM. Interestingly, the DR scenario shows reduced electricity consumption for most of the day compared to the scenario without DR.

The Figure 13 represents the three different load profiles for a power plant. The 2-MVar load is represented by load profile 1. Situated near the terminus of the 14-kilometre feeder, it is probably inductive and uses reactive electricity. The 250-kW load is represented by load profile 2. It uses actual electricity when connected to the 100kVA transformer and can mean a variety of equipment kinds. A 2-MW load is represented by load profile 3. It is the most significant load in the system and is shown as the lowest load on the diagram. It also uses a substantial quantity of actual electricity.

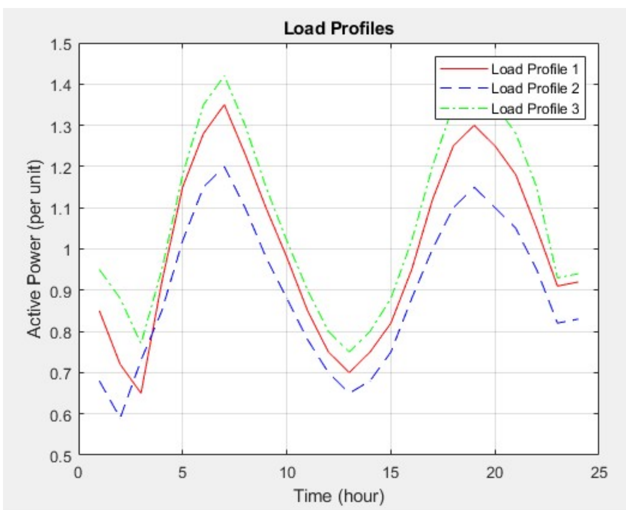

Figure 13. Active Power for different loads

4.2. Performance analysis

Metrics like voltage imbalance, THD and power loss are employed as a measurement in terms in this section to assess and contrast the proposed method's efficiency with existing methods such as Improved Lightning Search Method (ILSM) [26], Particle Swarm Optimal Placement (PSbOP) [27], Quantum Based Dragonfly Optimization (QbDO) [28], Optimized Re-phasing Technique (ORPT) [29] and Micro Grid Energy Management System (MG EMS) [30]. The reason for choosing these approaches for comparison validation is the hybrid model and recently implemented approaches. This existing approach contain the optimal model for regulating the grid performance, but due to improper and desired less tuning, average performance was scored compared to the proposed model. In addition, the compared algorithms were tested in the same proposed platform with the same simulation settings given in Table 1, and the performance was compared to each other.

4.2.1. THD THD is the typical voltage and current variance brought on by the DC grid system's frequency fluctuation. It is the distortion measurement shown in the waveforms. It is brought on by nonlinear loads converting AC to DC. The DG system's current flow is maximized by this harmonic distortion, raising the conductor and transformer temperatures. The THD can be measured using the Eqn. (5).

$$THD = \sqrt{\frac{\sum_{H=2}^{n}(V_H + I_H)}{V_l + I_l}} \times 100 \tag{5}$$

Where H denotes the harmonic order I and V represents the current and voltage.

The THD percentage gained by the existing models is PsbOP 2.4%, ILSM 4.89%, and the proposed ZbDBNM model earned 2.3%. Thus, compared to the other methods, the proposed method's THD is relatively low. It displays superior performance. The statistics are revealed in Figure 14. Table 2 describes the overall THD assessment.

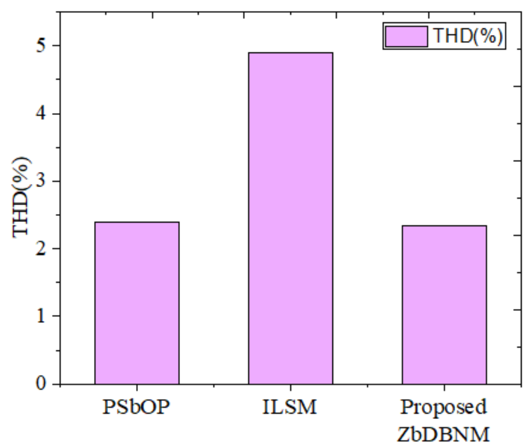

Figure 14. THD assessment

Table 2. Overall THD assessment

Methods	THD (%)	Std deviation	Confidence interval
ILSM	4.89	2	±1
PsbOP	2.4	4	±2
Proposed	2.32	1	±0.5

4.2.2. Voltage imbalance Voltage imbalance is the term used to describe the voltage variance in the energy system. It happens when the phase angle and voltage variances between them are not equal in magnitude. In unstable settings, it monitors the voltage difference between the three phases. The voltage imbalance can be calculated using Eqn. (6).

$$VI = \frac{\text{Maximum deviation}}{\text{Average voltage of 3 Phases}} \tag{6}$$

The voltage imbalance over time of a proposed model and the existing models are compared in Figure 15. The QbDO model earned 0.03%, the ORPT model earned 0.01298%, and the proposed model gained 0.01% of voltage imbalance. It shows that the proposed model generated better-balanced voltage output, which is crucial for the integrity of the power system. Table 3 offers the voltage imbalance assessment.

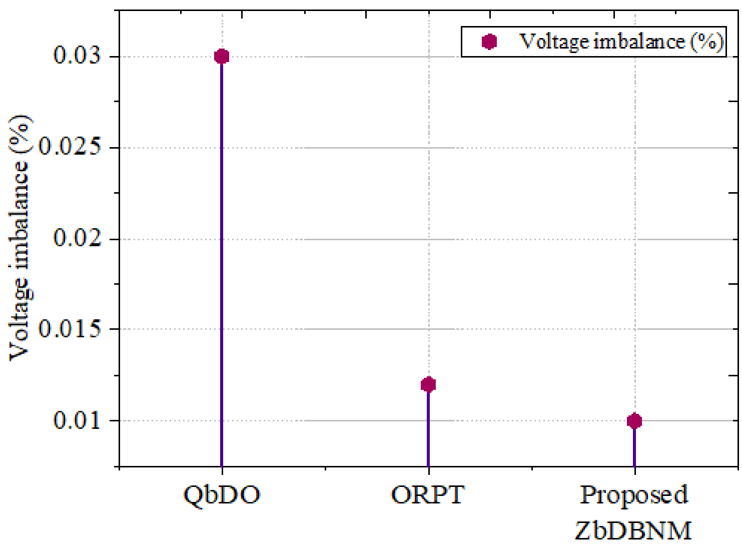

Figure 15. Voltage imbalance assessments

Table 3. Voltage imbalance comparison

Models	Voltage imbalance (%)	Std deviation	Confidence interval
ORPT	1.298	3	± 1
QbDO	3	2.5	± 2
Proposed	1	1	± 0.5

4.2.3. Power loss The efficiency indication of a system is power loss, which ought to be minimized to preserve Energy. By calculating the Power lost during energy conversion and transmission, this statistic evaluates the efficiency of the microgrid system. It could be calculated using the variation in Power between the total input and output. The calculation of the power loss can be expressed in Eqn. (7).

$$P_{Loss} = P_{Total} - P_{Output} \tag{7}$$

Where P_{Output} indicates the actual Power used or output by the system, P_{Loss} represents the power loss inside the system, and P_{Total} is the total Power injected or provided into the DC microgrid system.

Figure 16 shows the comparison of power loss. The MG EMS method earned a power loss of 3.76 watts, and the proposed ZbDBNM model made 2 watts. When comparing power loss to the existing model, the proposed ZbDBNM method performs better and has much less power loss.

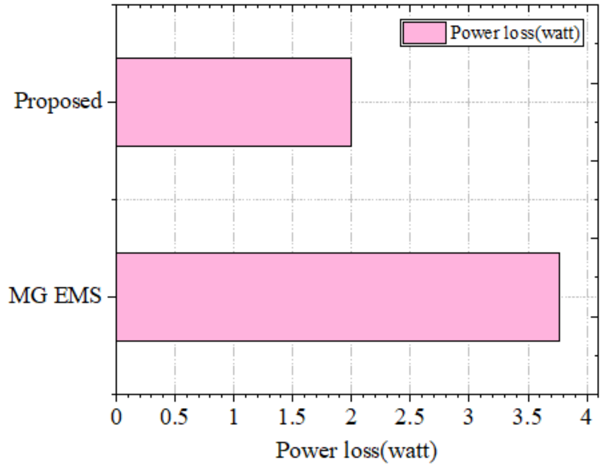

Figure 16. Power loss assessments

4.2.4. Power consumption Power consumption in a microgrid is the rate at which electricity is extracted from a particular source to meet demand inside the borders. The power consumption can be calculated using the Eqn. (8).

$$P_n = T_t \times C_n \tag{8}$$

Where P_n represents the power consumption of energy resource n T_t s, the total demand within the microgrid at a time t, and C_n the contribution factor of energy resource i s.

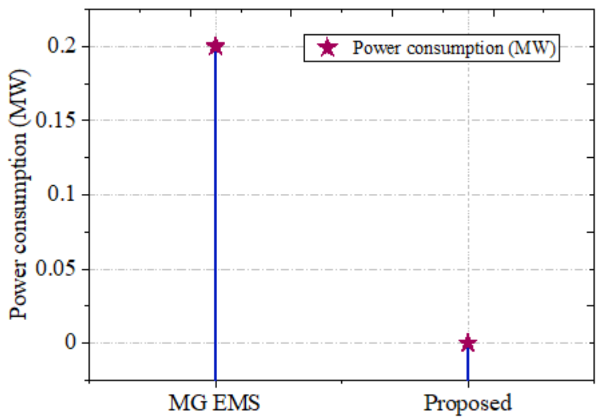

Figure 17. Power consumption assessments

The power consumption comparison is shown in Figure 17. The MG EMS method earned a power consumption of 0.2 megawatts, and the proposed ZbDBNM made -3.6082e-22 megawatts. Compared to the existing method, the proposed model rated lower power consumption. Table 4 details the power loss and power consumption comparison.

Table 4. Overall comparison of power loss and power consumption

Methods	Power loss (W)	Power consumption(MW)	Std deviation	Confidence interval
MG EMS	3.769	0.2	3.2	± 1
Proposed	2	-3.6082e-22	0.5	± 0.5

4.3. Discussion

It is where the DG concept was first designed. Additionally, the fitness function is used to forecast the values of the operating parameters, and the unique ZbDBNM system is activated to assess THD, power loss, and energy cost. The proposed ZbDBNM employed the Zebra optimal solution method to track the ideal energy cost, power loss, and THD reduction. To improve the proposed work further, understanding the negative power consumption is the most needed task, so negative power consumption was validated in Figure 18.

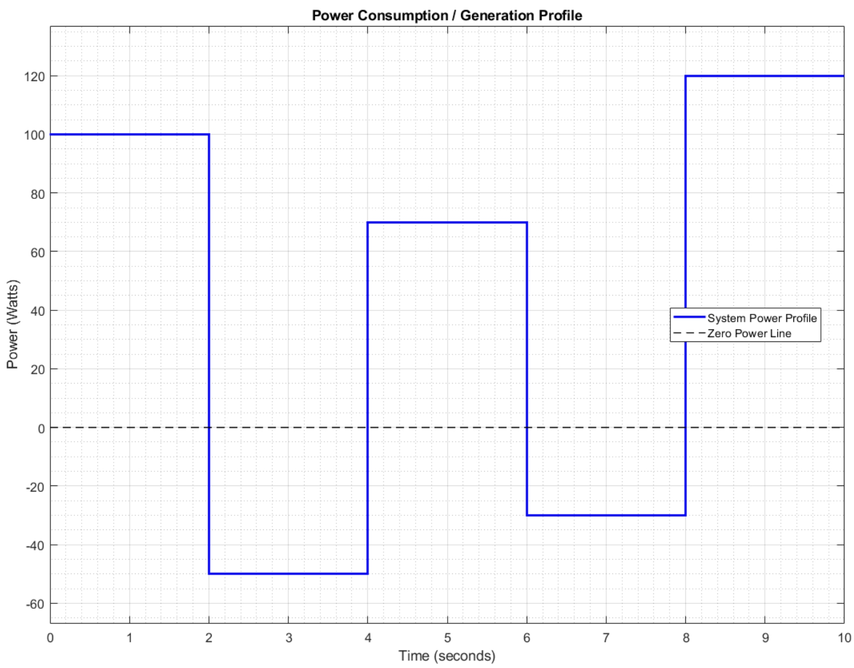

Figure 18. Negative power consumption

In order to check the robustness of the proposed novel solution, two different environments like rainy and cloudy were considered and the scalability performance was measured, which is exposed in Figure 19.

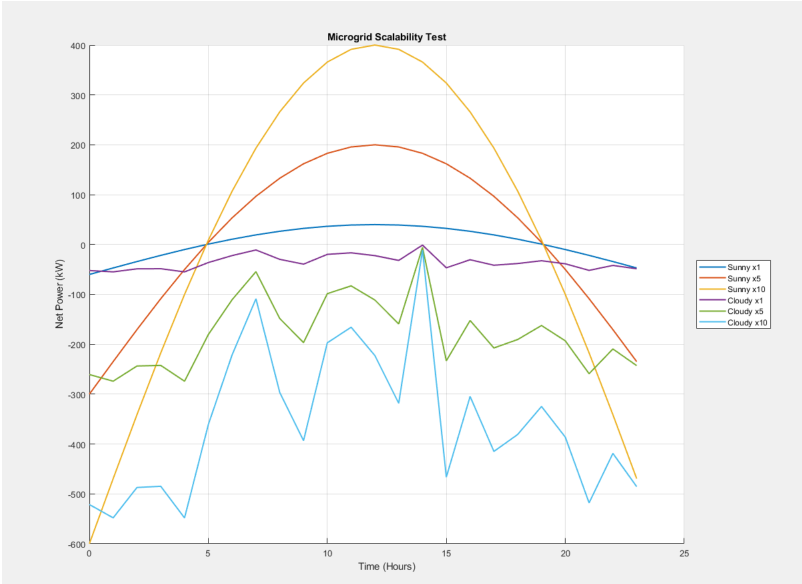

Figure 19. Scalability performances against rainy and cloudy environments

The sensitivity score of the novel solution is measured in different cases, such as sudden load change and renewable generation changes. Hence, the maximum frequency deviation was measured as a standard deviation parameter, which is explored in Figure 20.

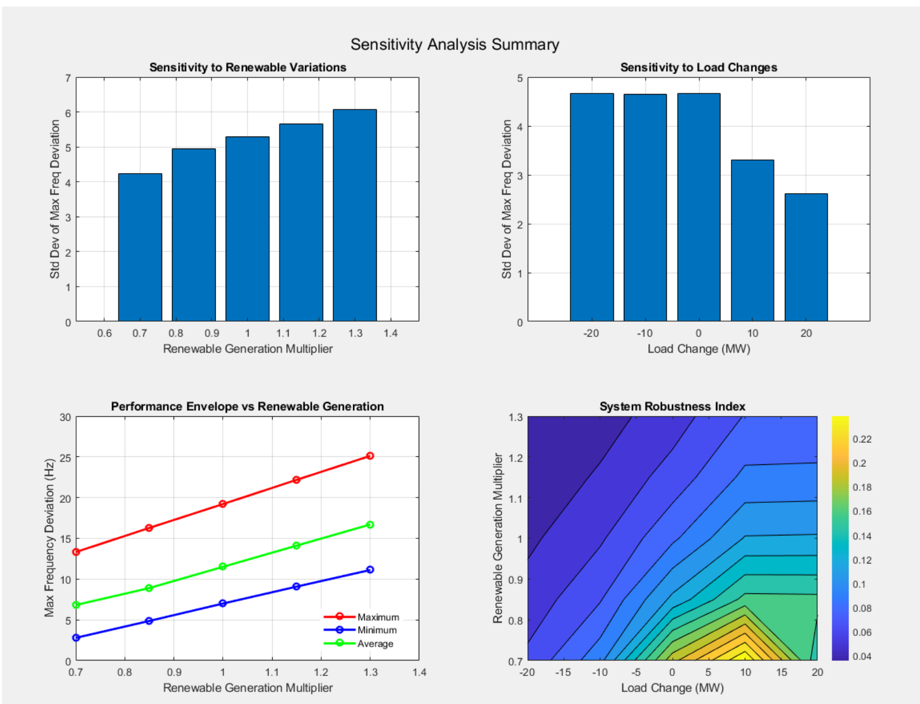

Figure 20. sensitivity analysis

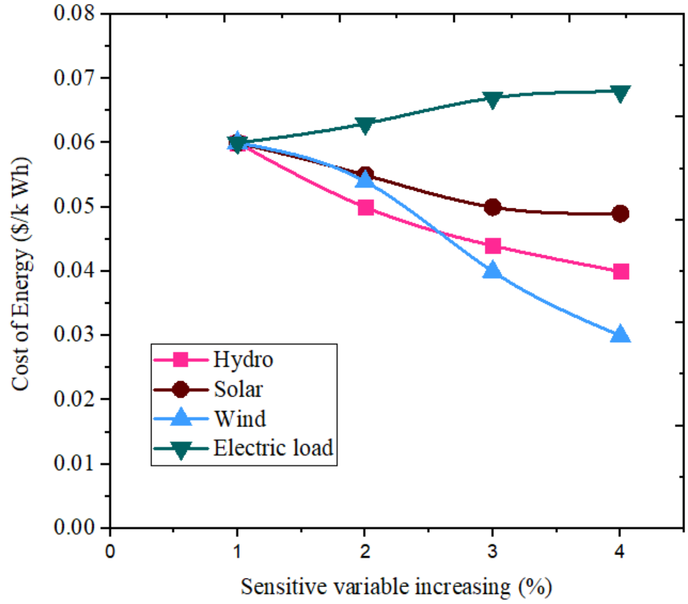

Figure 21. Cost of Energy versus sensitive variables

The cost of energy analysis with different renewable resources and electric load with the increment of sensitive variables is exposed in Figure 21.The reason for choosing specific zebra optimization has to be justified strongly against another optimization approach. So, the comparison was made with different optimization and zebra optimal models, and it is exposed in Table 5.

Table 5. Optimization performance

Methods	Accuracy	Execution time (ms)
PSO	85	438
GA	74	96
GWO	82	534
Flying fox	76.8	98
Zebra optimization	88.5	45

The proposed model produced 2.32% THD and 1% voltage imbalance. Furthermore, there is less power loss and consumption than the current approaches. The vital benefit of the designed method is that it finds and returns the best values faster and increases system efficiency. In addition, the proposed method decreases the memory utilization and design complexity compared to the existing model. Additionally, to prove the efficiency of the proposed model, the results are assessed for a few existing techniques such as recurrent with long short-term memory (RLSTM) [1], multiagent reinforcement learning (MRL) [3], Multiple-Decoder Transformer (MDT) [4], and Attention Dilated Residual Convolutional Network with Flying Foxes (ADRCNF) [5], and the results are shown in the Table 6. Here, the outcomes are obtained by processing the real-time California data from the energy government site (Final Project Report, Microgrid Analysis and Case Studies Report).In addition, all benchmark methods were executed and compared in the same proposed platform with same execution parameter constraints in Table 1.

Table 6. ZbDBNM performance comparison with real-time data

	RLSTM	MRL	MDT	ADRCNF	GA	PSO-LSTM	GWO	PSO	GWO-DBN	Proposed
Power loss (W)	7.2	4.1	8.5	5.6	6.7	4.9	11	24	19	2
Power Consumption(kW)	3.1082 e-16	3.8025 e-16	3.2045 e-16	3.0095 e-16	3.8095 e-16	3.9085 e-16	3.7834 e-16	3.8493 e-16	3.9365 e-16	3.6082 e-16
THD (%)	4.12	2.95	4.85	3.68	8.2	7.4	9.4	6.2	6.6	2.32
Voltage imbalance (%)	2.8	1.6	3.2	2.2	3.4	4.5	5	6	3.5	1
Energy cost ($)	16.9	13.7	18.5	15.3	17	34	23.1	20.9	18	12
RME	12	22	4.5	6.1	9.2	17	12.4	7	4.3	3
MAE	11.3	20	5	7	10	13	12	6.8	4.1	2.8
Execution time (ms)	125	97.3	113	89	96	102	534	438	123	45
Optimization accuracy (%)	91.3	94.5	92.8	95	74	86.5	82	85	90	98.4
Std deviation	1.9	5.8	7.4	6	2	4.8	3.5	4.5	0.5	0.5
Confidence interval	±1	±1.5	±1	±2	±1	±1	±1.5	±2	±1	±0.5
P-value	0.004	0.007	0.005	0.008	0.09	0.009	0.07	0.08	0.05	0.002

The performance is shown in the Table 6 identify the better performance of the ZbDBNM over other existing models, such as RLSTM, MRL, MDT, and ADRCNF. The reason behind the implementation of DBN in the proposed ZbDBNM framework is their ability to model sophisticated power system dynamics effectively. In contrast to traditional models, DBN is capable of learning deep representations of nonlinear relationships in energy consumption patterns effectively and is thus well suited for power flow prediction and optimization in a dynamic smart grid setting. In addition, the incorporation of the Zebra fitness function improves optimization by dynamically adapting control parameters to ensure low energy losses and better harmonic distortion levels. These findings illustrate the performance of ZbDBNM in providing enhanced grid stability, greater efficiency, and reduced operations costs, making it a solid alternative to conventional predictive and optimization models.

5. Conclusion

Creating and developing an intelligent distributed energy system that integrates electric vehicles, BESS, and renewable energy sources represents a significant advancement in energy optimization. Concerning regulating the cost of Energy, power loss and THD, the ZbDBNM exhibits potential by conforming to given thresholds. The ZbDBNM algorithm's fitness process attained the optimal price of Energy, power loss, and THD. The approach is simulated, and its performance is evaluated using the MATLAB environment. The ZbDBNM methodology is compared with the previous control methods and validated in terms of THD, cost and power loss to validate the performance increase. The ZbDBNM model yielded a THD of 2.32%, less than the existing models. The ZbDBNM generates 2W of power loss, which is less when compared to the current models.

Furthermore, the ZbDBNM lowers the energy cost of the system by $12. Consequently, the recommended control method has worked well. Hence, the present model is well suited for the large grid real-time data. However, it is not tested for the real-time hybrid renewable resources microgrid data. In addition, the challenge for processing the proposed system in the time hybrid renewable resources microgrid data in practical is poor scalability and memory resources. Based on the different scenario at the regular time interval, the voltage imbalance and error occurrence was occurred, on that time, the scalability get disturbed. Moreover, the required memory sources weren't able to estimate due to the dynamic environment. Also, implementing the proposed model in the practical data might suffer from lack of communication due to the sensor noise. In future, implementing the intelligent system along with optimal signal processing system with filtering concept would beneficial for the communication improvement. In addition, the intelligent model is employed for managing the scalability and activating the memory resource monitoring in the computing edge system could reveal the finest outcome further.

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Not applicable
Conflict of Interest
Not applicable
Data Availability
Not applicable
Consent to Publish
Not applicable
Authors Contribution
Mr. Anish Vora and Dr. Rajendragiri Aparmathi - have contributed equally to the work.

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