

Energy Optimization Of Distributed Energy Resources In Microgrids For Ev Charging Stations

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ABSTRACT

It is imperative that more study be done on energy optimization in microgrids with distributed energy resources (DERs), especially as renewable energy sources like solar and wind power grow in popularity. There is a lot of promise for increasing grid reliability, cutting costs, and improving efficiency by incorporating artificial intelligence (AI) tools into this process. The intricate optimization challenge in DER management is resolved by AI approaches including ant colony optimization (ACO), particle swarm optimization (PSO), and genetic algorithms (GA). It is still difficult to manage and optimize DERs when there are sporadic renewable energy sources present. The use of artificial intelligence (AI) approaches for microgrid energy distribution optimization is thoroughly reviewed and analysed in this work. The energy sources' cost-priority based energy management strategy (CEMS) for the SWEG model has been developed to charge the EVs. The proposed methodology is compared with that of the PSO and GA algorithms. The outcome shows that PSO optimization gives the best cost compared to GA. The amount of grid power used to drop by 37%, resulting in a 27.86 kg carbon dioxide reduction throughout the day. In this work, the use of a novel bio-inspired optimization method called the Zebra Optimization Algorithm (ZOA) for energy optimization in microgrids with distributed energy resources (DERs) is examined. The simulation analysis is done in MATLAB tool to see the effectiveness of the system accompanied with power loss, voltage imbalance and THD analysis. Case study is based on microgrid integrated with RES and BESS. .

Keywords: Microgrid, Distributed Energy Resources (DERs) Artificial Intelligence (AI), Energy Management System (EMS) Optimization, Load Forecasting, Renewable Energy, Smart Grid.

INTRODUCTION

A microgrid is a localized grid that can function either separately or in tandem with the larger grid. A range of DERs, including solar panels, wind turbines, energy storage systems, and even traditional generators, are usually included. Distributed energy resources are small-scale power generation or storage technologies that are integrated into the grid at the distribution level. Electric vehicles (EVs), battery storage, and photovoltaic systems are a few examples. Microgrids are made to supply electricity to certain areas or establishments, including hospitals, universities, military installations, or isolated settlements. The capacity of a microgrid to function independently from the main grid is its distinguishing characteristic. A microgrid can "island" itself in the case of an outage or other disturbance in the wider grid, ensuring that its loads get uninterrupted electricity. Because of this feature, microgrids are essential for improving sustainability, resilience, and energy dependability.

Microgrids are important components of contemporary energy systems for a number of reasons that listed below.

Resilience and Reliability: Microgrids offer a dependable and robust power supply for vital infrastructure, particularly during grid disruptions or natural disasters.

Decentralization of Power: By enabling power generation to be decentralized, microgrids ease the burden on centralized grids and enable energy production and consumption to occur closer to the point of need.

Integration of Renewables: By making it easier to integrate renewable energy sources like wind and solar, microgrids help businesses and communities lower their carbon footprint.

Energy Cost Management: Demand-side management, load shifting, and a decreased reliance on pricey peak power from the main grid are some ways that microgrids can lower energy costs by controlling local generation, storage, and demand.

Advanced power electronics and artificial intelligence (AI) methods are taking over electrical grids, and this trend might last for many years [1]. Modern AI techniques are being used in MG controls more and more, which is important because it facilitates the seamless integration and disconnection of distributed generation (DG), enhances end-user power quality, and.

increases power system transient stability. Because of this, MGs are emerging as a reliable and greener energy source. By highlighting the autonomy of the local energy supply, MGs that are primarily constructed with distributed energy resources (DERs), also known as DGs, and renewable energy sources (RESs), like wind turbines and photovoltaics, can integrate DERs with conventional energy sources like diesel engines and

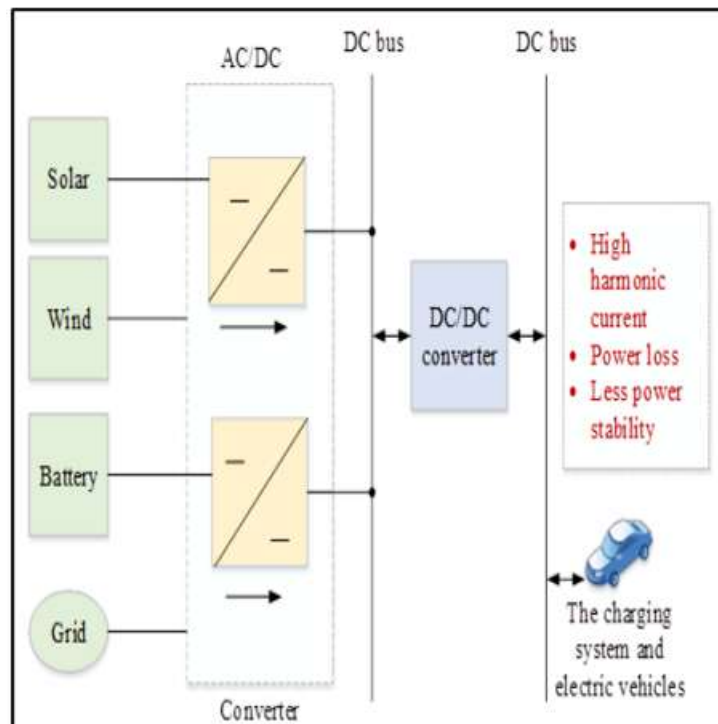
combustion gas turbines. Deep learning (DL) and machine learning (ML) are significant subcategories of artificial intelligence [4]. ML and DL models can typically be classified as either supervised or unsupervised based on the input training data. A complex approach that uses data-driven modelling in addition to the physical model is needed for system control and analysis in order to better address the observability and controllability issues in the context of microgrids [5].

Numerous control levels are available in the microgrid hierarchical control system, contingent on the functionality to be addressed while accounting for control volume, communication requirements, and energy resources. By integrating AI techniques with these current schemes, a microgrid environment can be managed and run more precisely, quickly, and efficiently [6]. However, before a significant number of MGs powered by renewable energy sources can be incorporated into the current electrical network, a number of issues still need to be fixed. Several studies provide different approaches to address the different control problems that microgrids (MGs) bring up while maintaining the quality of the energy generated. Among the artificial intelligence-based control strategies that are receiving increased attention are neural networks (ANN), fuzzy logic (FL), genetic algorithms (GA), particle swarm optimization (PSO), metaheuristic techniques, grey wolf optimization, ant colony optimization, neuro-fuzzy inference systems, and evolutionary algorithms [7]. Intelligent controllers are particularly well-suited for these types of applications because they can adapt to uncertainties and be used in circumstances when the exact model of a system is unavailable or subject to change. With the use of modern power electronics-based technologies, the microgrid can offer increased energy efficiency, higher power supply quality, and improved service reliability [8–10]. To increase the electrical system's dependability and performance, storage systems must be added to the integrated systems. The batteries are charged using the extra energy generated by the integrated sources, and in the case of a production shortage, the batteries are charged using the stored energy. An energy management system is utilized for demand-side and energy flow management, accounting for supply and demand fulfilment, operational limitations, and economic considerations [11].

For example, [12] used a mixed-integer linear programming method to optimize the capacity and installation position of energy storage equipment in DES, which significantly improved the economic performance of the energy storage system. To attain a relatively quick convergence rate, [13] suggested a predetermined time optimization technique for distributed generators. In order to solve the distributed microgrid system connected with photovoltaic (PV) cells, wind power, and hydrogen energy storage with a configuration scheme, [14] examined distributed power generation with uncertainties using a conditional value at risk approach and a Bonferroni test.

Improved the smart grid model by adding RES and putting an expanded optimal variation technique into practice [15]. This research article's main contribution is the development of a novel smart grid framework that makes use of renewable energy sources and artificial neural networks (ANNs) to efficiently control voltage levels and guarantee the best possible distribution of reactive power within grid networks. In order to manage power in Microgrids (MGs), Ant Colony Optimization (ACO) was used [16]. This approach took into account a number of factors, including economic considerations, fuel and resource availability, environmental constraints, and multifaceted goals. In order to overcome the difficulties presented by complex multi-objectives and multi-constraints in energy management, the study proposed the application of the constraint satisfaction problem (CSP) technique. [17] suggested a hybrid approach that includes the use of renewable energy sources (RES) in order to attain the best possible performance and cost-effectiveness in electrical frameworks. The bacterial foraging optimization algorithm (BFOA) and artificial neural network (ANN) approaches are combined to create the hybrid approach. In this article, authors have mentioned the strategy of AI technique based on Zebra optimization algorithm. The utilization of this method improved the voltage balance, power loss and THD values compared to PSO and other algorithms to check the effectiveness and validity of the performance in MATLAB tool. The system is taken by RES and BESS to manage and control the operation of the microgrid.

2.PROPOSED MICROGRID SYSTEM



. Figure.1: Proposed microgrid schematic diagram

Figure-1 is showing the schematic diagram of our research microgrid system. This system consisted of solar PV, wind turbine (small) and battery as energy storage device. All sources are used in small power rating in grid connected microgrid. Both sources are renewable type generation while conventional battery storage is also taken to fulfill the lagging power amount in needs. The power generation from solar PV and battery are in DC manner but for wind turbine it is in AC manner. The microgrid is connected with utility grid system. Here, for an instance EV car is taken to charge and discharge at the consumer side of the grid. The purpose of this microgrid is to fulfill the charging of the EV car which is directly connected with DC bus. To stabilize the generation of the sources, the AC-DC and DC-DC converters are connected to the main DC bus. Also, EV car is connected to the DC-DC converter through DC main bus. This is the construction of the microgrid that authors have proposed in this work. Some researchers have addressed the issues of power balance, grid stress, charging costs, and uninterrupted charging during the variable load of electric vehicles at a charging station. In [2], a rule-based energy management scheme was proposed, in which an if-then rule was developed by considering six modes of energy flow for uninterrupted charging of electrical vehicles. It was noted that the uninterrupted charging of electric vehicles at a constant price is no longer guaranteed using PV and ESU alone; the integration of other renewable sources such as wind, tidal, and biomass with PV is the best suitable solution for the effectiveness of the proposed system. In [3] the game theory approach and stochastic dynamic programming was proposed for lowering the charging cost of EVs. The motive to reduce additional cost or penalty and to appease the intermittent nature of the RESs a game with mixed strategy developed in decentralized system [4]. The time-based use-based demand response Programme by mixed integer programming was developed to reduce the operating costs of electrical vehicles [5]. Overall, most of the researchers focus on EV charging cost minimization, but no one has deployed energy management strategy based on a daytime hour-by-hour assessment of renewable energy availability for the new EVCS model known as the 'SWEG' (Solar PV-WIND-ESU and grid) model of EV charging station. In very rare work, Financial Models presented.

The key points of this paper are:

- to achieve economical charging of EVs
- to reduce consumption of grid power for EVCS to maximize profit
- to achieve an economical charging of EVs and
- to make Charging station Environment Friendly

Objective Functions

The cost of acquiring energy from the grid and ESU discharge are included in the objective function, as well as the profit gained from EV charging and surplus energy supplied to the grid. The best cost function for the system is as follows:

$$\text{Best Cost} = C_{\text{Purchase}} - C_{\text{sell}}$$

$$C_{\text{Purchase}} = \sum_{t=1}^N P_{\text{grid}}(t)(C_{-t}) + P_{\text{ESU-DI}}(t)(C_{-s}) \quad (1)$$

$$C_{\text{sell}} = \sum_{t=1}^N P_{\text{ev}}(t)(C_{-ev}) + P_{\text{RES_Surp}}(t)(C_{-g})$$

System Architecture

The system is comprises of solar PV, Wind energy, Energy storage unit and grid. The electrical vehicles are the plugged as a load.

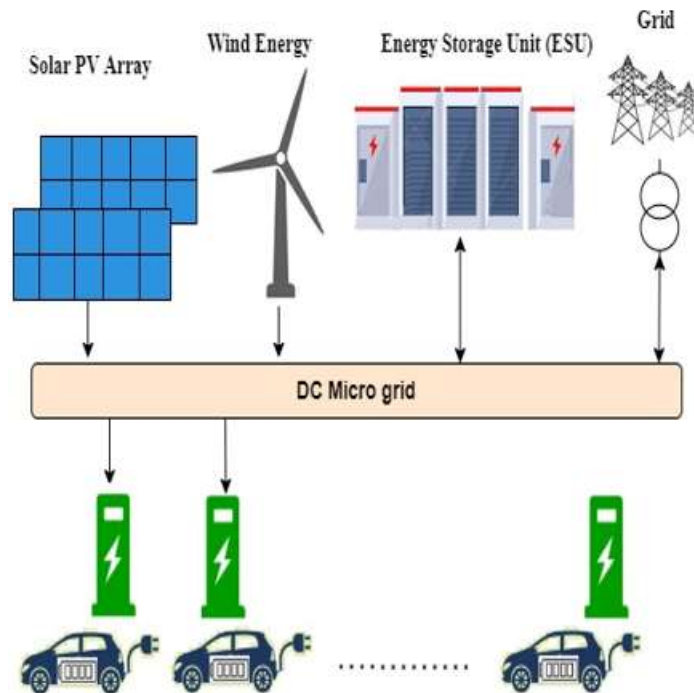


Figure 2. .Architecture of proposed system

The charging station designed for maximum 10 charging points.

Solar PV System

The electrical power generated from fix angle solar PV array depends on the irradiation and temperature at a site; the solar PV array is series-parallel connected group of modules.

In this paper, for the assessment of Solar PV power throughout the day, an average plane of Array Irradiance (W/m^2) and temperature ($^{\circ}\text{C}$) data for the period of one year from 1/1/2021 to 31/12/2021 of Bhuj, Gujarat, India location of latitude 23.2420°N and longitude 69.6669°E taken from the NREL [34]

Eq. (2) shows the power output from solar PV array on the basis of Irradiance and temperature [35].

$$P_{\text{pv}} = Y_{\text{pv}} f_{\text{pv}} \left(\frac{G_{\text{T}}}{G_{\text{T_STC}}} \right) [1 + \alpha_{\text{p}} (T_{\text{C}} - T_{\text{C_STC}})] \quad (2)$$

Where;

Y_{pv} = Rated capacity of PV system in KW at STC

f_{pv} = loss factor in %, assumed 12.29 %

G_{T_STC} = Irradiance of 1000 W/m² at STC

α_P = power temperature coefficient [%/°C]

T_c = the current temperature of a PV cell [°C]

T_{c_STC} = the temperature of the PV cell under regular test conditions (25°C).

Wind Energy Conversion System

The wind speed at a location determines whether or not wind turbines can generate electricity; the force of the wind turns the turbine's rotor blades, which are coupled to a generator by the turbine shaft. Wind turbine operates between cut in and cut off speed and power output constrained by their physical limits.

In this paper, the wind speed data of a site Bhuj, Gujarat, India at latitude 23.2420° N and longitude 69.6669° E is acquired from the daily wind speed of one year (from 1/1/2021 to 31/12/2021) under the NASA Prediction of Worldwide Energy Resource at 10 Meters Hub Height [36]. Eq. (3) shows the power output of a wind turbine based on wind speed [37];

$$P_w = \begin{cases} 0 & v \leq v_c \text{ or } v \geq v_o \\ P_r * \frac{v^3 - v_c^3}{v_r^3 - v_c^3} & v_c \leq v \leq v_r \\ P_r & v_r \leq v \leq v_o \end{cases} \quad (3)$$

Where P_r = rated wind power

v_c = cut-in wind speed;

v_r = Rated wind speed and

v_o = cut-off wind speed.

3. Controlling Strategy

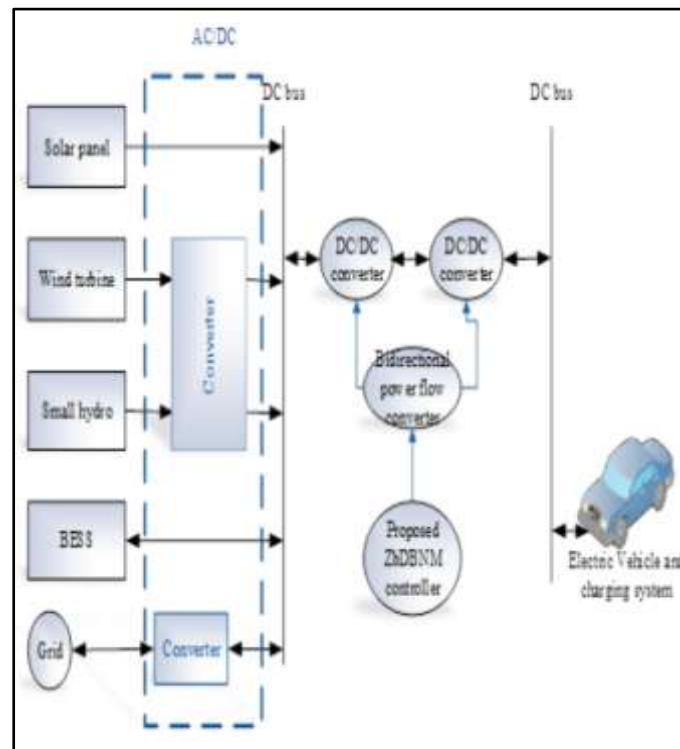


Figure.3: Control architecture

Solar energy, wind energy is converted into electricity. To achieve desired output up to the consumer, end the whole system comprises various components. Different components like dc-to-dc converter, harmonic analyzer is used to achieve exact amount of power loss or voltage stability. Zebra optimization algorithm helps to optimize various parameters. Various parameters of microgrid system like power generation capacity according to available source intensity, energy storage capacity, power and voltage handling depends on types of loads is controlled by ZbDBNM. Also, constraints generated by converter-inverter, environmental parameters ensure the operational efficiency of microgrid system using this system. Because of the limitations of distributed energy resources like solar, wind instability of voltage may arise. It can be maintained with this type of algorithm. Using solar or wind power generation faces the problem of voltage reliability and stability due to they are variable with respect to time. Bidirectional controller solves these difficulties along with the ZbDBNM algorithm. ZOA and Artificial Intelligence (AI) techniques are combined in this study to enhance DER management, energy dispatch, and load forecasting. Small-scale energy generation or storage devices near the loads they service are known as distributed energy resources, or DERs. DERs are essential to microgrid operation since they allow for increased energy sustainability and autonomy.

Solar PV panel: One of the most popular renewable energy sources for microgrids is solar power. When paired with energy storage devices, solar panels may produce a steady source of energy by converting sunlight into electrical power. Particularly helpful for cutting greenhouse gas emissions and operating expenses is solar electricity.

Wind turbine: Another essential renewable resource for microgrids is wind energy, especially in regions with strong winds. Wind turbines use the wind's kinetic energy to generate electricity. Similar to solar, wind energy is sporadic but can provide a substantial contribution to a microgrid's mix of renewable energy sources.

Battery storage system: Batteries or energy storage devices are essential for controlling the unpredictability of renewable energy sources like wind and solar. When demand is high or renewable generation is low (for example, on overcast or quiet days), excess energy produced during times of low demand can be stored and used later.

Electric car/vehicle: Electric cars can function as mobile distributed energy resources (DERs), adding to a microgrid's energy mix and supplying extra storage. EVs can store extra energy and even return power to the grid when necessary if the proper infrastructure is in place.

Localized energy generation is made possible by DERs, which improve energy resiliency and lessen dependency on centralized power plants. DERs contribute to energy independence and the reduction of greenhouse gas emissions by combining storage and renewable energy sources. They are also essential in demand-side management, which lowers costs and increases grid stability by optimizing energy use to match generation.

Optimization challenges:

Notwithstanding its advantages, microgrid energy resource optimization poses a number of difficulties, especially given the intermittent nature of renewable energy, peak load control, and energy storage constraints. The intermittent nature of renewable energy sources, including wind and solar, is their biggest drawback. Whereas wind energy fluctuates based on wind speed and availability, solar energy is exclusively available during the day and is affected by weather. In order to guarantee a steady energy supply, this intermittency makes real-time energy management more difficult and necessitates sophisticated forecasting methods and reliable energy storage systems. While based on artificial intelligence load forecasting can assist in anticipating renewable energy generation and energy demand, managing volatility is still a difficult task. A microgrid's energy consumption can fluctuate greatly throughout the day, therefore controlling peak demands is essential to preventing system overload. Demand for power may outstrip available generation capacity during peak hours, necessitating load shedding, the use of backup generators, or the importation of energy from the main grid. Maintaining stability, cutting operating expenses, and minimizing grid dependency all depend on DERs being optimized to handle peak demand.

Because energy storage systems have a limited capacity, controlling when to charge and discharge them is essential to achieving microgrid efficiency. The charge-discharge cycle results in energy loss, which may lower system efficiency overall. Inappropriate charging cycles can hasten the deterioration of batteries. Batteries must be stored properly to increase their longevity and guarantee their availability when needed. Using AI approaches, the charging and discharging cycles can be optimized based on projections of renewable generation and demand.

Methodology

A cost-priority-based energy management strategy (CEMS) is used to charge the electric vehicles. Electric vehicle demand, the amount of energy stored in the ESU, and accessible renewable energy are all taken into consideration while planning charging operations. When an electric car charging station's owner sells extra energy back to the grid, they are paid. Although

there is no fee involved with charging an ESU, because of battery deterioration, the ESU's discharge costs are seen as an energy purchase since they are free of charge. Additionally, the cost of obtaining grid energy is taken into consideration.

The optimization takes care of the charging and discharging of an energy storage device. This suggested study utilises the PSO optimization technique. The problem of multi-source renewable energy system optimization has been addressed by accomplishing the objective function and taking into account all restrictions, such as generation–demand balance, energy storage unit charging and discharging and the level of charge of ESU and EVs.

Energy Flow Modes:

No load

$EV_{load} = 0$, $P_{RES} > 0$, $ESU < ESU_{max}$

It is assumed that there are no EVs for charging between 2 and 4 p.m. at night and that RES power is available due to wind energy system and energy storage unit partial discharge; in this scenario, energy flows from RES to ESU to charge the ESU batteries. In same mode whenever ESU is fully charged,

The RES power exported to the grid for revenue generation.

Under load

$EV_{load} < P_{RES}$, $ESU = ESU_{max}$

During the day between 12 to 15 pm, the energy accessibility from RES sources is higher than the required EV load, and ESU is at its maximum level. In this mode, energy flows from RES to EVs, and surplus energy from RES is exported to the grid.

In second

$EV_{load} < P_{RES}$, $ESU < ESU_{max}$

In same above mode, When ESU is not at its maximum level then Energy flow from RES to EVs, Surplus Energy from RES delivered to charge ESU.

$P_{RES} > EV_{load}$ and ESU , $ESU < ESU_{max}$

In this case RES power is higher than ESU and EVs and if ESU is partial discharged then First Energy flow from RES to EVs, Surplus Energy from RES delivered to ESU and grid.

Overload

$EV_{load} > P_{RES} + ESU$, $ESU = ESU_{max}$

In this mode, Energy flow from RES and ESU to charge EVs and deficit Energy taken from grid. Modes are; $P_{RES}2EV$, $ESU2EV$, $PG2EV$

$EV_{load} > P_{RES}$, $ESU < ESU_{max}$

In this mode, Energy flow from RES and Grid to EVs. Modes are; $P_{RES}2EV$, $PG2EV$

Optimization:

The Genetic Algorithm (GA) is a type of metaheuristic search algorithm. Genetic Algorithms (GAs) Natural selection and the fundamentals of genetics underpin its operation. In this work it is implemented for optimize renewable power and charge discharge of ESU.

Partial Swarm Optimization (PSO):

PSO, or particle swarm optimization, is a form of stochastic optimization that mimics the behaviour and intelligence of swarms. The following parameters considered;

There is a maximum of 300 iterations allowed

Swarm Size (Population Size): 1000

An object's weight in inertia

A weight damping ratio of 0.99 is used for the inertia weight.

Personal Learning Coefficient $C_1=1.5$:

$C_2 = 2.0$: Coefficient of global acquisition of new knowledge.

4. Optimization Process

The core aim of the research work is to implement optimal microgrid operation, in order to reduce harmonics, power loss and reduce voltage instability in the proposed microgrid system in presence of RES and BESS or in general DER. This is multi-function optimization problem that formulated based on multi-constraints. In order to formulate objective function, following formula and constraints are used as below.

$$O_{pt} = f \sum_{i=1}^n \frac{Pl * \frac{Ce}{\log_{10} \sqrt{THD}} + \frac{\sqrt{Pl}}{THD^2} - \frac{Pl * Ce * THD}{100}}{\text{multi-function optimization}}$$

Here,

P_l = power loss,

C_e = stability constant

THD = total harmonics distortion

The voltage and power from generation sources are concerned in optimization process. The constraints are used in this article are listed as below.

$$V_{min} \leq V(i) \leq V_{max}$$

$$P_{min} \leq P(i) \leq P_{max}$$

Here,

V = voltage of system

P = power of system

To solve this equation Zebra optimization algorithm (ZOA) is developed in his research work by authors.

Zebra Optimization Algorithm (ZOA) :

Simulating the social behaviour of zebra herds in the wild is the fundamental concept of the Zebra Optimization Algorithm (ZOA). During the foraging process, a pioneer zebra helps other zebras migrate in the direction of the food source. Consequently, as the herd of zebras crosses the plains, the pioneer zebra leads the pack. Zebras use their zigzag running pattern as their primary defence against predators. Sometimes, however, they congregate in an attempt to frighten or confuse the predator. The mathematical modelling of these two forms of intelligent zebra behaviour serves as the primary source of inspiration for the suggested ZOA architecture. The population of ZOA, a population-based optimizer, includes zebras. From a mathematical point of view, every zebra represents a possible solution to the problem, and the plain in which the zebras are found is the search space for the problem. Each zebra's position within the search area determines the values for the decision variables. As a result, each zebra can be described as a member of the ZOA using a vector, whose elements indicate the values of the problem variables. The zebra population can be mathematically modelled using a matrix [18].

$$Z = \begin{bmatrix} Z1 \\ \vdots \\ Zi \\ \vdots \\ Zn \end{bmatrix} = \begin{bmatrix} Z11 \dots Z1j \dots Z1m \\ \vdots \\ Zi1 \dots Zij \dots Zim \\ \vdots \\ Zn1 \dots Znj \dots Znm \end{bmatrix}$$

n= the number of population members (zebras).

m= the number of choice variables.

Z= the zebra population.

zi = the i^{th} zebra.

The beginning points of the zebras inside the search region are selected at random. The ZOA population matrix can be expressed as follows. Each zebra represents a possible fix for the optimization problem. Therefore, the objective function may be evaluated using the recommended values of each zebra for the issue variables. By comparing the values acquired for the objective function, which efficiently analyses the quality of their related candidate solutions, the optimal candidate solution for the given problem is found. In minimization problems, the optimal zebra is the one with the lowest objective function value. Conversely, in maximizing problems, the zebra with the highest objective function value is the best candidate. Since the placements of the zebras and, consequently, the values of the target function are changed in each iteration, the optimal candidate solution must be identified in each iteration. Two of the zebra's natural actions have been used to update ZOA members. Foraging is the first of these two behavioural patterns, while predator protection strategies are the second. As a result, the ZOA population is updated twice during each cycle.

Each zebra represents a possible fix for the optimization problem. Therefore, the objective function may be evaluated using the recommended values of each zebra for the issue variables

$$F = \begin{bmatrix} F1 \\ \vdots \\ Fi \\ \vdots \\ Fn \end{bmatrix} = \begin{bmatrix} F(Z1) \\ \vdots \\ F(Zi) \\ \vdots \\ F(Zn) \end{bmatrix}$$

To implement zebra optimization algorithm, here flowchart is presented in figure-4. The stepwise procedure is explained as under.

The first step is to identify the DC microgrid setup which is consisted with solar PV, wind turbine and battery storage system. In second step, the condition of battery storage is decided that depends on charging and discharging condition. According to generation sources, the zebra optimization algorithm is programmed in MATLAB tool (coding). This controller is used to control the microgrid operation under given constraints in order to reduce harmonics, power loss and voltage instability.

By this AI technique, anticipation of the power loss, stability and THD can be identified. If all conditions and constraints of the system are satisfied then this algorithm run successful and can generate the results in MATLAB. To validate the results this method is compared with other methods also to check the result and convergence speed.

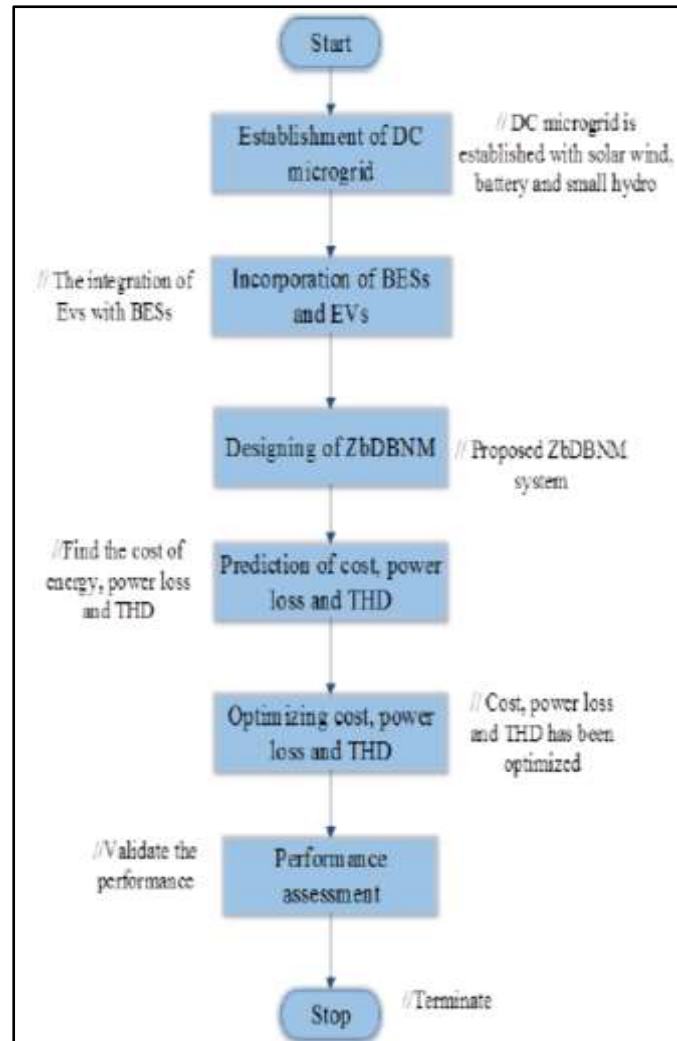


Figure.4: Algorithm of Zebra optimization method

5. System Parameters

The data used in MATLAB programming is presented in tabular form.

Table 1. Solar PV system Parameters

Parameter	P _{pv}	Module Type	W _p	N _p	N _s
Unit	KW	--	Watt	--	--
Value	120	Polycrystalline	305	40	10

Table 2. Wind turbine parameters

Parameter	P _r	v _c	v _r	v _o	H _h
Unit	KW	m/s	m/s	m/s	m
Value	50	3	10	15	10

Table 3. Solar PV power forecast data

Time (Hr.)	Avg. Plane of Array Irradiance (W/m ²) G	Avg. Cell Temp of Year (C)	PV Power System (kW)
0	0.00	24.4	0.00
1	0.00	24.0	0.00
2	0.00	23.7	0.00
3	0.00	23.4	0.00
4	0.00	23.1	0.00
5	0.00	22.9	0.00
6	2.14	22.7	0.22
7	79.47	24.8	8.39
8	306.51	33.0	33.50
9	535.18	42.5	60.87
10	723.42	50.5	84.97
11	838.59	55.8	100.55
12	881.13	58.1	106.60
13	843.60	57.5	101.81
14	735.74	54.3	87.72
15	582.54	49.2	68.08
16	383.67	42.3	43.59
17	174.94	34.2	19.22
18	28.20	28.6	3.03
19	0.06	27.4	0.01
20	0.00	26.7	0.00
21	0.00	26.0	0.00
22	0.00	25.4	0.00
23	0.00	24.9	0.00

Table 4. Wind power forecast data

Time (Hr.)	Wind Speed Forecast (m/s)	Output Power of the Wind Turbine (kW)	Total RES (KW)
0	4.5	16.47	16.47
1	4.4	15.97	15.97
2	4.4	15.32	15.32

3	2.9	0.00	0.00
4	4.2	13.91	13.91
5	4.2	13.16	13.16
6	4.3	14.91	15.14
7	4.8	20.40	28.79
8	5.1	24.95	58.45
9	5.0	22.42	83.29
10	5.0	22.31	107.28
11	5.0	22.89	123.44
12	5.1	23.75	130.36
13	5.2	25.33	127.14
14	5.3	26.85	114.57
15	5.3	27.70	95.78
16	5.2	25.09	68.69
17	4.9	21.64	40.86
18	4.7	19.16	22.19
19	4.6	18.35	18.35
20	4.6	17.85	17.85
21	4.5	17.14	17.14
22	4.5	16.78	16.78
23	4.5	16.72	16.72

Table 5. ESU parameters

Parameter	P _{ESU}	I	η	Initial SOC	Final SOC
Unit	KWh	Ah	%	%	%
Value	40	250	95	10	90

Table 6. Electric Vehicles Parameters

Parameter	4V_B C	N _{max}	Initial SOC	Required SOC
Unit	KWh	Number	%	%
Value	25	10	30	80

6. Results and Discussion

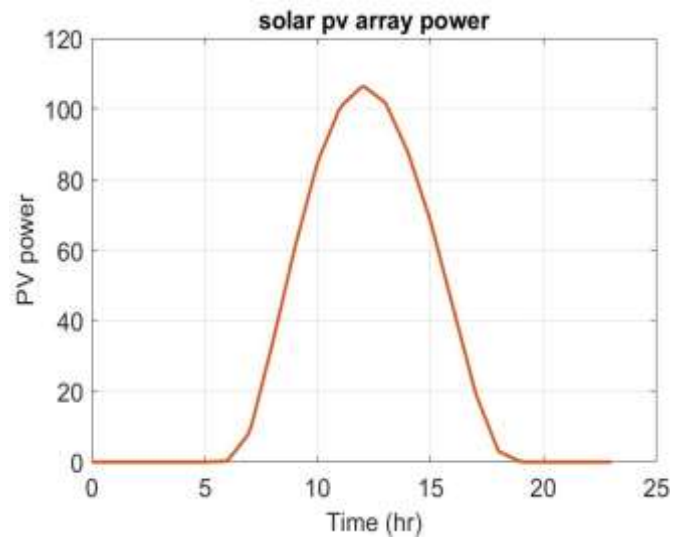


Figure 5. Solar PV Power

The forecasted PV power throughout the day is obtained maximum 106 KW at peak irradiation time

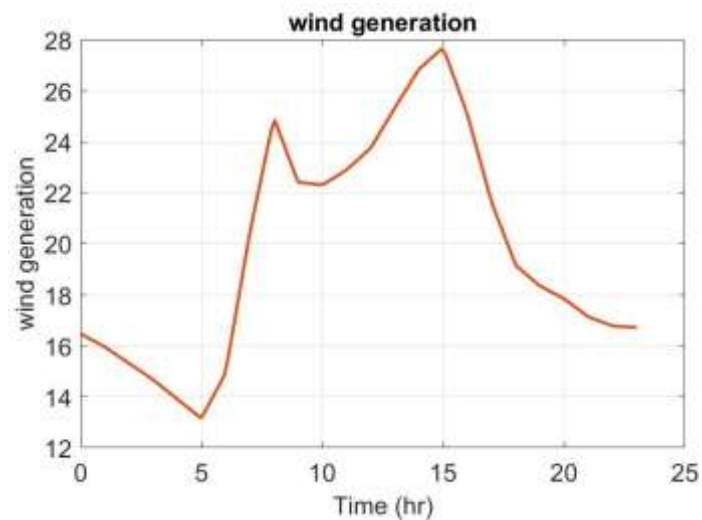


Figure 6. Wind Power

The wind power throughout the day is obtained maximum 27.70 KW at peak wind speed at 10m hub height.

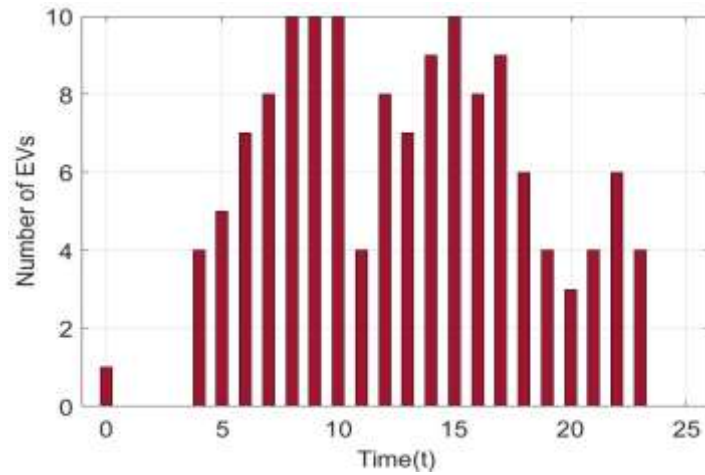


Figure 7. Number of EV plugged

The numbers of EV plugged for the charging is assumed accordance to existing vehicles fuel filling trends at fuel station.

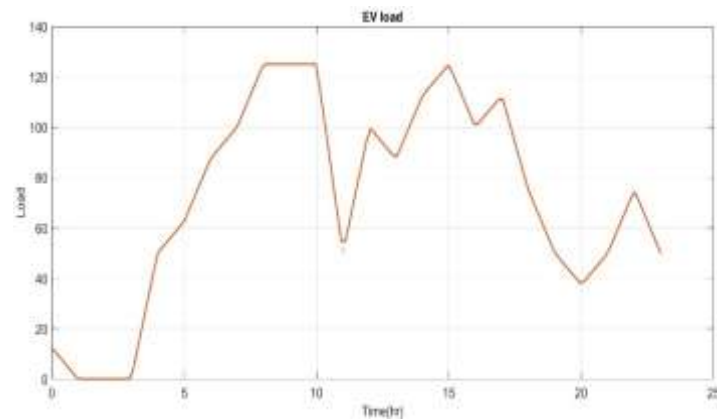


Figure 8. EVs load

The real-time EV load corresponded to battery capacity and SOC are presented here; during rush hour, e.g., office time between 9:00 am and 11:00 am in the morning and 5:00 pm in the evening, more EVs are plugged into the system for charging.

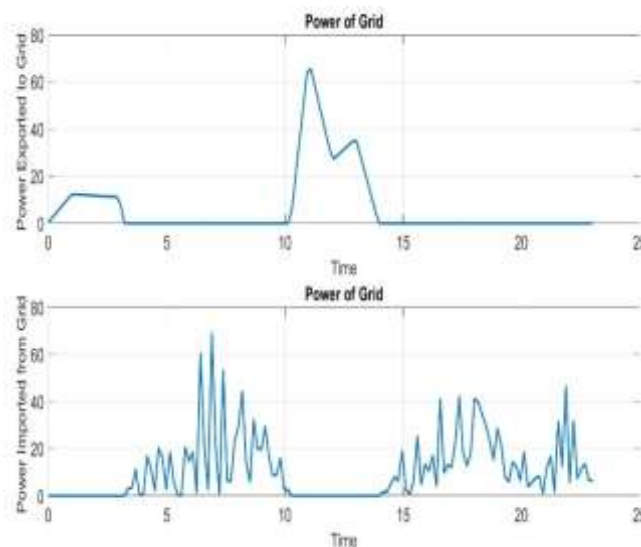


Figure 9. Grid Power export and import

When RES power is greater than required demand, the surplus renewable power is exported to the grid. As a result, it can be seen that during the morning when there is no EV load, surplus power of 3.97 KW at 1 am, a maximum of 60 KW at 11 am, and an average of 37.48 KW from 12 to 15 pm is exported to the grid. Total of 133.44 KWh of energy exported to the grid throughout the day. The deficit power is taken from the grid for the uninterrupted charging of EVs. Average of 46.28 KW imported between 4 a.m. and 10 a.m. In the other slot between 15 pm and 23 pm, 36.18 KW of power was drawn from the grid. Hence, during the day, 520.19 KW of power was imported from the grid.

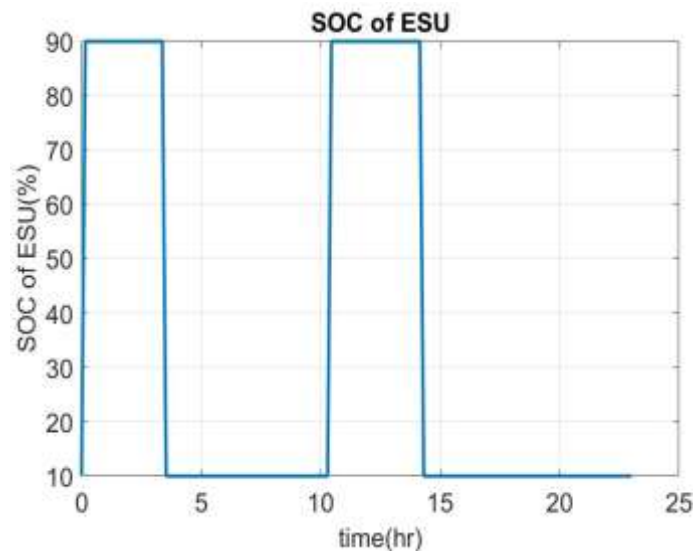


Figure 10. Charging-discharging SOC of ESU

The ESU charging discharging SOC set at 10 to 90 percent initial and final respectively. Results show ESU charge and discharge twice in day from the surplus renewable power.

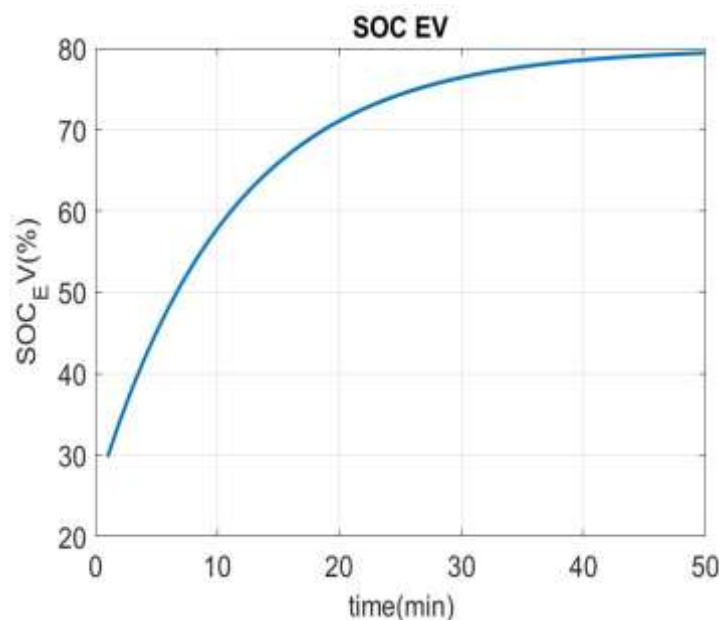


Figure 11. EV Charging SOC

The average SOC of all EVs considered 30 to 80 percentages initial and required respectively. Result shows that EV charged from 30% to 80% SOC in 50 minutes time.

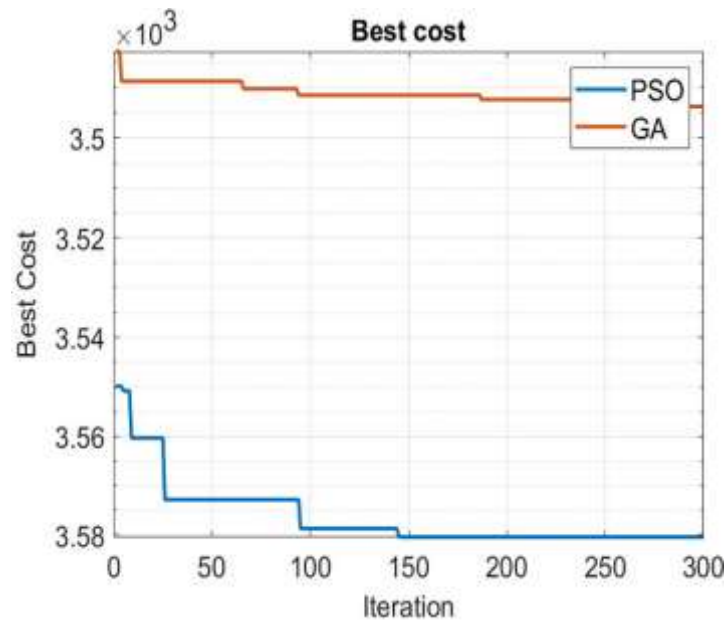


Figure 12. Best Cost with PSO

As per designed cost priority-based energy flow modes, the best cost from the buying and selling of energy including ESU discharge cost as buying energy is found INR 3580.00.

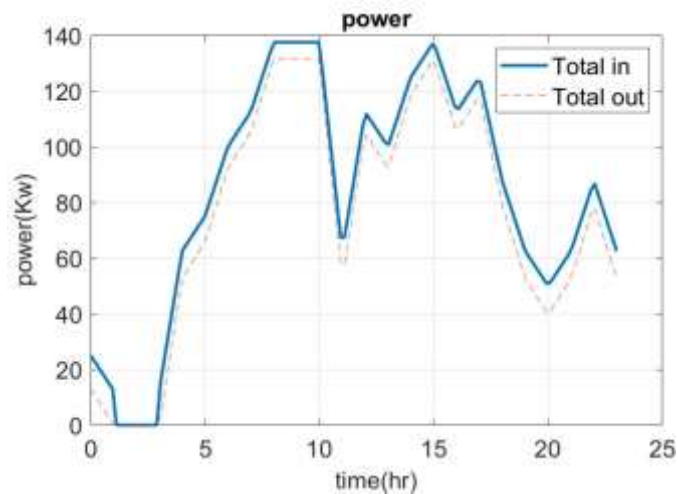


Figure 13. Power Balance

The power balance between generation and EVs load found nearly equal to same. The system power throughout the day is presented in financial analysis.

Table 6. Financial Analysis

Parameter	Grid Connected charging station	Proposed SWEG model for EV Charging station		
	Grid	RES	ESU	Grid
Number of EVs charge per day	137	137		

EV Charging Price (INR/KWh)	4.4	4.4		
Total Energy Consumed by EVs in KWh/day	1712.5	1130.31	62	520.19
Total Rupees of Energy Purchased (INR)	6850.00	--	205.84	2600.00
Amount of Surplus Energy sale to grid (KWh)	--	133.44	--	--
Revenue from energy sale to grid (INR)	--	133.44* 2.25(Rate) = 300.24	--	--
Revenue from energy sale to charge EVs (INR)	7535.00	7535.00		
CO2 Reduction in Kg/day	--	34.80.	--	--
Daily Profit (INR)	658.00	3580.00		

7. CASE STUDY

The system is simulated in MATLAB tool by taking solar PV, wind turbine and battery storage system. The zebra optimization algorithm is implemented in this control strategy to optimize the microgrid operation by considering total harmonics distortion (THD), power loss and voltage instability. The proposed optimization algorithm is effective in this system and has speedy convergence rate compared to conventional optimization algorithms. The MATLAB performance is presented in this section. The parameter of the proposed system is described in below table. This is based on actual meteorological data for wind and solar power

This simulation also takes into account the battery's capacity, state of charge (SOC), and charging/discharging efficiency.

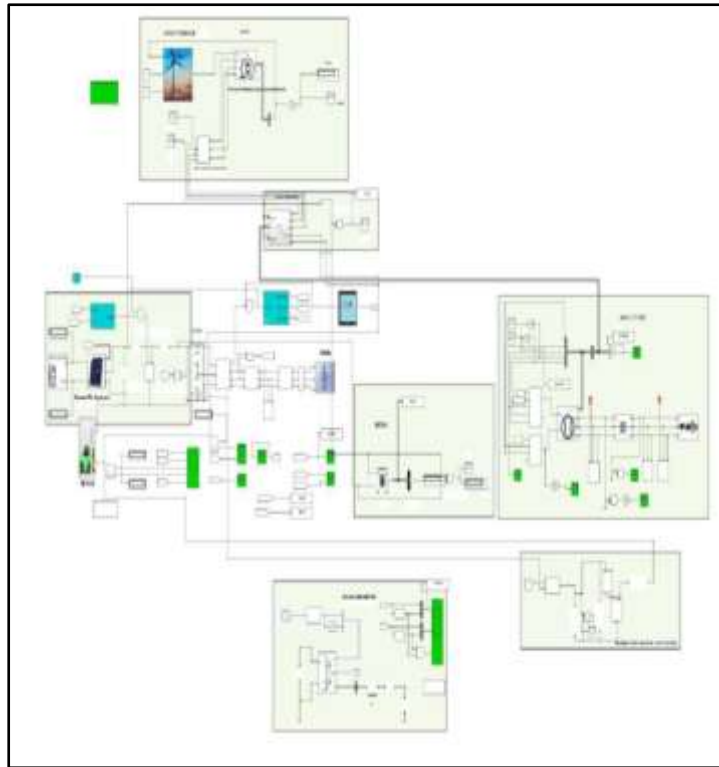


Figure.14: Case study system in MATLAB

Parameters	Description
Platform	MATLAB Version R2021a
Optimization	Zebra
Population	30
Iteration	100
Base MVA	1 MVA
Base kV	11kV
Solar Irradiance	1000
Maximum power	1.2 kW
Panel Temperature	250C
Output voltage	300V
Wind speed	2.5m/s
Maximum power	2.5kW
Cut off speed	22m/s
Cut in speed	7m/s
Output voltage	500V
Power and X/R	20kW and 0.7
Load	9 kW and 11.25 kVAr

Grid voltage and current	300V and 2A
Real power	1.1 p.u

The obtained results with this case study system is shown as below.

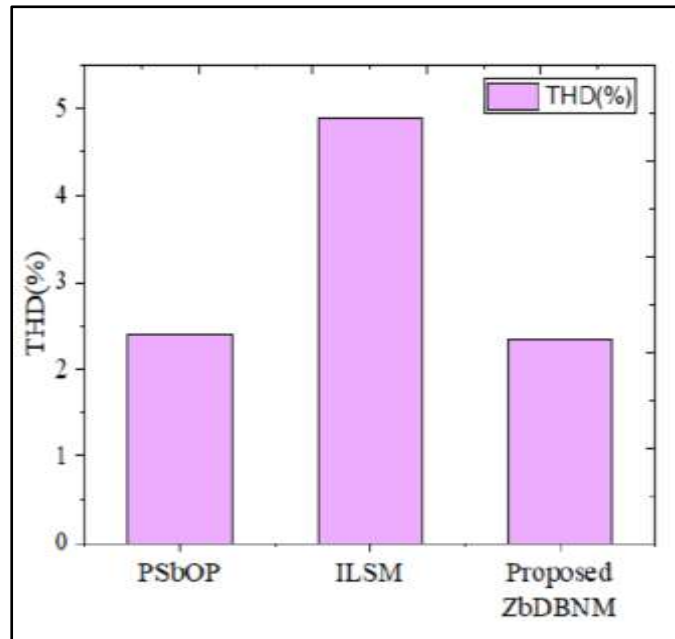


Figure.16: THD analysis in MATLAB

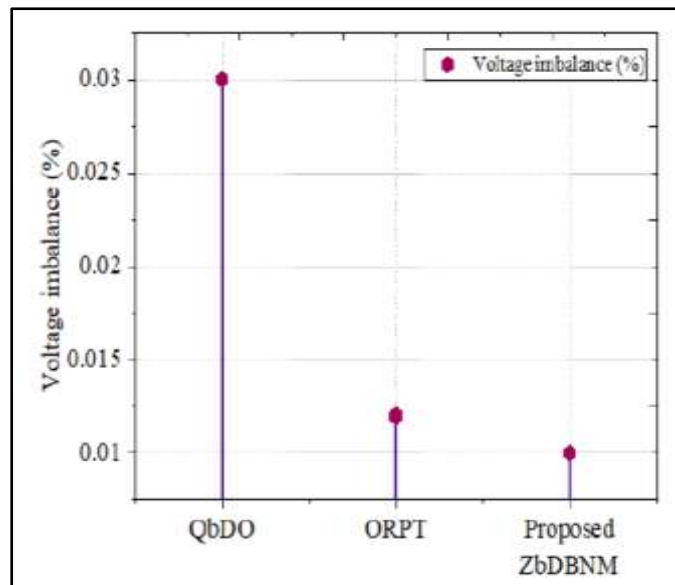


Figure.17: Voltage stability analysis

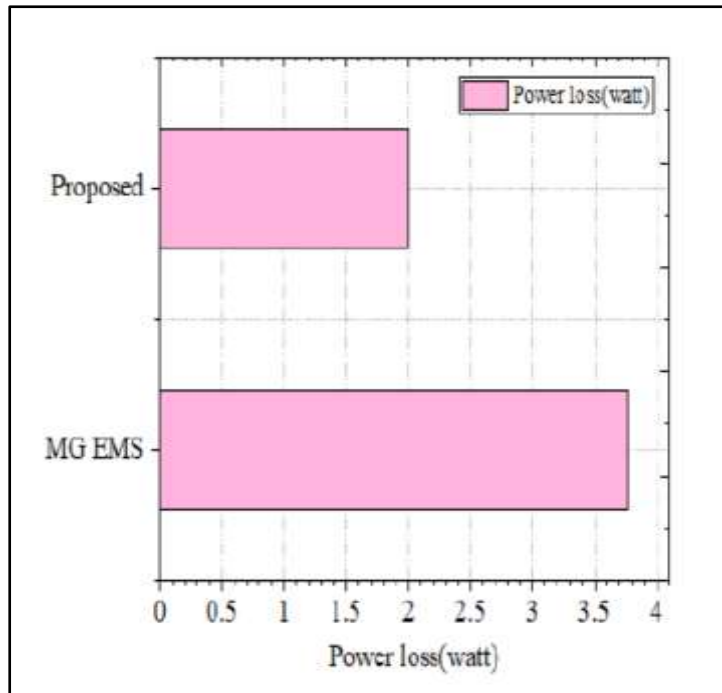


Figure.18: Power loss (watt)

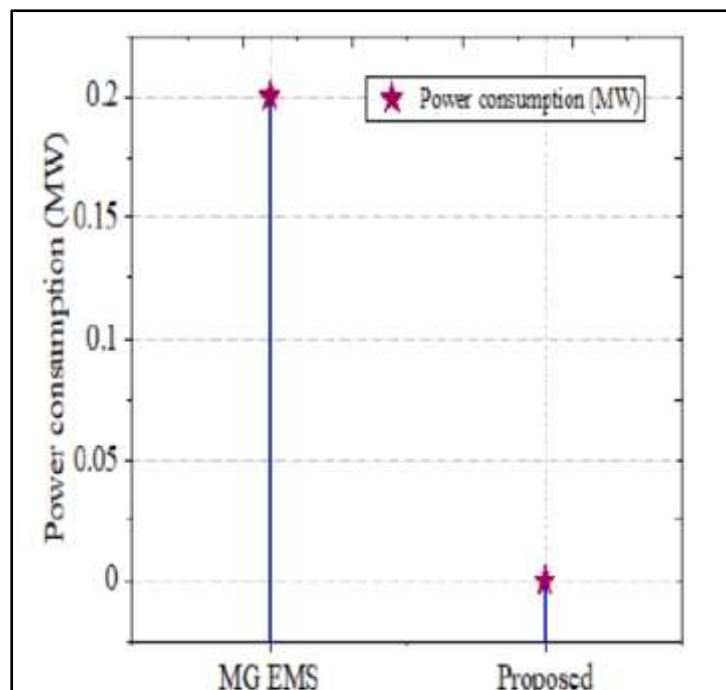


Figure.19: Power consumption analysis

The optimal price of energy, power loss, and THD was reached by the fitness process of the ZbDBNM algorithm. The MATLAB environment is used to simulate the method and assess its effectiveness. To verify the performance improvement, the ZbDBNM methodology is compared to the earlier control techniques and verified in terms of THD, cost, and power loss.

8.CONCLUSION

ZOA's optimum energy dispatch schedules are examined for various time periods. The findings demonstrate that ZOA can dynamically modify energy dispatch in response to projections of load and renewable generation, guaranteeing a low dependency on backup generators. A viable approach to energy optimization in microgrids with Distributed Energy Resources (DERs) is the Zebra Optimization Algorithm (ZOA). It works effectively in the dynamic context of a microgrid because it may swiftly converge to an ideal solution while striking a balance between exploration and exploitation. Its efficacy is further increased by integrating AI approaches, especially in load forecasting. According to simulation data, ZOA performs better than conventional optimization techniques in terms of efficiency, cost reduction, and the use of renewable energy. This study has certain limitations as well. The accuracy and application of the results may be impacted because the optimization models and algorithms employed in the study are predicated on oversimplified assumptions that may not match the real situation. Highlight the importance of AI in optimizing DERs in microgrids and provide a summary of the study paper's main conclusions. Future research might concentrate on expanding AI methods to larger grid systems, enhancing cybersecurity, or incorporating new DER kinds

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