International Journal of Advanced Technology and Engineering Exploration, Vol 11(116)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2023.10102555

Research Article

Electric vehicle with smart grid integration using a hybrid honey badger algorithm and artificial neural network

Abdul Khadar Asundi[1*], Abdul Lateef Haroon Phulara Shaik[2], Syed Mohiuddin[3], Naseeruddin[2] and Farzana Begum Kalburgi[4]

Professor, Department of Electrical and Electronics Engineering, Ballari Institute of Technology and Management, Ballari, India[1]
Associate Professor, Department of Electronics and Communication Engineering, Ballari Institute of Technology and Management, Ballari, India[2]
Associate Professor, Department of Mathematics, Ballari Institute of Technology and Management, Ballari, India[3]
Assistant Professor, Department of Electrical and Electronics Engineering, Ballari Institute of Technology and Management, Ballari, India[4]

Received: 05-December-2023; Revised: 18-July-2024; Accepted: 20-July-2024

Abstract
Electric vehicles (EVs) are a specific class of vehicles that use one or more electric motors to create propulsion. Numerous recent research studies have focused on energy storage systems (ESS) as a major research area. However, as EV usage grows, there are several challenges related to the electricity required for charging that result in peak demand of smart grids with EV stations. The probable impacts of integrating EVs and photovoltaic (PV) into the grid, on certain individuals, are the subjects of numerous researches. The main motivation for PV's incorporation in grid-to-vehicle (G2V) and vehicle-to-grid (V2G) services is to provide supplementary power services to preserve the grid stability. PV arrays have to meet one more need before they choose to offer V2G services. Controlling the power between different load and source conditions requires a number of analyses. Therefore, a hybrid intuitive model was developed that implements a honey badger algorithm and artificial neural network (HBA-ANN) controller to balance grids and frequency. With the inclusion of PV generation, the proposed HBA-ANN optimizes the G2V or V2G outline of the EVs using dynamic programming. The result analysis clearly shows that the proposed HBA-ANN controller's overall efficacy surpasses that of existing controllers based on artificial neural network-based particle swarm optimization (ANN-PSO) and resettable integrator (RI). The evaluation, conducted in terms of overall harmonic distortion, power loss, and efficiency, demonstrates that the proposed HBA-ANN controller achieves 3.26%, 0.186 kW, and 97.14%, respectively.

Keywords
Artificial neural network, Electric vehicle, Energy storage system, Honey badger algorithm, Photovoltaic, Smart grid.

1.Introduction
The rapid development of electric vehicles (EVs) has placed a significant pressure on the necessity of establishment of an efficient control framework for the power grid system [1]. The electrical grid is put under an inordinate amount of stress during the EV charging process, which causes voltage fluctuations and supply shortages [2]. As the number of plug-in electric vehicles (PEVs) grow, so does the growing demand for internal combustion engines, which are used to drive vehicles. PEVs have larger storage batteries than the latest models of energy vehicles, such as blended EVs, which makes them suitable for taking part in grid-to-vehicle (G2V) or vehicle-to-grid (V2G) [3]. Technological solutions to the operational and environmental problems that existing energy systems experience, are found in the integration of renewable energy sources and EV into power grids [4].

Achieving sustainable development goals, especially those related to lowering carbon emissions and improving energy efficiency, depends heavily on this integration. With the help of technologies like V2G and G2V, EVs are considered as dynamic energy storage alternatives in addition to being a means of mobility [5]. The integration increases their ability to

*Author for correspondence

control grid loads and power balance, which strengthens and stabilizes energy systems. The prior researches wherein several industries and information technology architectures connected to smart systems, are not actually in line with certain standards [6]. Successful EV management is capable of improving the dependability and steadiness of power systems [7]. Additionally, it makes possible the use of sources like imperishable energy and increases the system effectiveness entirely [8]. Also, this EV has the potential to improve dependability and stability of electricity networks [9]. Additionally, the energy storage system (ESS) operation and supervision in standalone power systems are made possible by the energy management system (EMS) [10]. As a specialized electricity load, EVs are used as mobile storage devices to help with load balancing in the power grid [11]. Furthermore, advancements in EVs help and affect the grid in a number of ways, such as reactive power compensation, load levelling, peak load shaving, voltage as well as frequency regulation, and smooth incorporation of renewable sources. It does, however, have certain detrimental effects on the grid [12].

According to recent studies, EVs are clearly superior to other conventional energy-efficient devices in terms of ease of use and environmental friendliness. Due to their increased efficiency, EVs are probably going to become more and more popular, particularly in urban cities [13]. Electrical drives powered by batteries, petrol or semiconductors also possess the ability to provide 60 Hz frequency range. Recently, many decision-making applications have shown the effectiveness of the model-free methodology [14]. It does not require previous system knowledge; instead, it picks up a good control technique and uses it to respond correctly for achieving the desired outcomes [15]. The batteries of EVs used as storage along with two-way converter, are hardly ever recorded. When employing EVs as an ESS, high-power rapid charging is advocated [16]. Previously V2G researches were conducted at a smart-grid facility intended to support the production of electricity from variable renewable energy sources. In addition to this, most published researches use both level 1 and level 2 charging for V2G technology [17]. Through V2G, excess electricity from EV is transferred to the smart grid. This innovative approach serves as a backup energy source and helps to meet the electricity demand during peak usage periods especially when weather-dependent renewable sources are unavailable. Collectively, these works significantly focus on advancements in the fields of charging development and the integration of renewable energy, thereby setting the direction of future study [18]. The creative approaches highlight the enormous potential for further developments in EV charging optimization through renewable energy integration, and thus, offer a variety of strategies and enhancements not found in the literature. They also significantly improve the economic and environmental performance of EV charging systems [19]. However, certain limitations are noted in the studies that currently exist, along with some challenges faced by developed nations with noticeably larger EV infrastructure, in terms of safety problems and infrastructure issues (development and management) [20]. Therefore, the major objective of this study includes performing state-of-the-art current research on energy management at different levels. These involve energy supply and demand organization at charging stations via optimization of smart grids, by EV charging control methods.

The contributions of this study are as follows:

- A review of various battery and load connection topologies by utilizing a range of models.
- An ESS, photovoltaic (PV) and EV energy distribution is suggested by the usage of an EMS called honey badger algorithm and artificial neural network (HBA-ANN).
- The direct current (DC) bus voltage and converter current are controlled by using the HBA-ANN approach. The DC bus voltage is stabilized by using HBA-ANN control strategy.

The organization of the rest of the manuscript is as follows: Section 2 explains the previous research conducted on the EMS present in EVs. Section 3 reports on the implemented HBA-ANN strategy. The findings and explanations of the results are presented in Section 4 and Section 5. Finally, the conclusion is stated in Section 6.

2.Related works

In order to ensure accurate and stable energy extraction through the PV approach, even under differing sunlight circumstances, Nouri et al. [21] demonstrated a V2G system accompanied by intuitive management and ANN combined with the particle swarm optimization (PSO) algorithm, which proved beneficial for the EV battery. The downy logic controller guaranteed that the batteries of electric-powered car were charged and discharged, and likewise, pre-arranged conditions have been used in conjunction with the constant voltage/constant current approach. But while EVs did not participate in management of energy, the energy ability depreciated, drawing attention to how crucial V2G functioning was. In these scenarios, the grid substituted for the scarcity of energy, which exactly was not advantageous, in the commercial aspect.

Cheng et al. [22] built a versatile switched reluctance motor (SRM) for plug-by Evs, using diverse handling and charging measures. In SRM, the motor handling mode was required to interpret the slow-down of the actions. The SRM windings were exploited to construct a periodic converter with PF control characteristics, to recharge the drive battery. The additional batteries were powered from the engine via an integrated half-bridge converter, but it produced higher loss.

A novel method known as dual four-quadrant operation, with bidirectional converter for EVs, was presented by He et al. [23]. The goal of the research was to keep the load side current constant, while an EV was charged and discharged. The chargers of EV systematically transferred the two electricity flows, active and reactive, between EV batteries and the grid, by using a model predictive control (MPC) technique. In addition to active power exchange, a brand-new mode known as vehicle-for-grid was introduced. However, it took so long (three cycles or 60 microseconds) to reply to a new instruction for the complete system.

Kanimozhi et al. [24] proposed an efficient two-stage model using a resettable integrator (RI) approach, through which power factor correction (PFC) and DC voltages were supervised and regulated. In order to help the remedy diodes and converter switches, zero voltage switching (ZVS) and zero current switching (ZCS) were employed in the next phase. But when the diode latency was taken into account, the switching loss increased.

A new technique called V2G was introduced by Justin et al. [25] using quicker charging battery. The EV batteries acted as capable and potential energy storage units in smart grids, which helped in the storage of additional useful energy with the aid of a small-scale power network. These batteries stored extra grid energy and returned it to the grid when required. A DC rapid charging station was part of the system for discharging the smart grid that was connected to the EVs. However, total harmonic distortion (THD) was obtained through a reliable inductor-capacitor-inductor (LCL) filter design. The harmonic error was restricted in this research while also following the Institute of Electrical and Electronics Engineers (IEEE) regulations.

The rule-based energy management strategy (RB-EMS) was developed by Alsharif et al. [26] to control the power flow in the system. The RB-EMS's precise response helped to meet the load demand as quickly as possible, at the lowest feasible operational cost. Still many arrangements were required to address the power quality problems in RB-EMS.

A bidirectional converter with high voltage gain was created by Heydari-doostabad and O'donnell [27], to be used for V2G and G2V applications. The suggested model had advantages over other converters, as it included a wider range of voltage and current, making its architecture more practical and flexible. Nevertheless, V2G had a restricted voltage range, lacking a common ground among the data, which necessitated the use of additional switches and capacitors.

The setup of a control for an EV charger that offered V2G services while reducing the current THD, was discovered by Gonzalez et al. [28]. The EV charger control's current loop gain was increased to reduce THD, but by doing so, the stability of the charger controller was compromised. However, more consideration was supposed to be focussed on the aim of preserving the existence of V2G.

For EV type applications involving on-board battery chargers, Ramos et al. [29] established a control method that reduced power wavelet of single-stage remote converter. This work offered a dominance method for reducing low-frequency variations in the power module, while maintaining overall dimensions and weight, without adding up current subordinate side elements. Nevertheless, the presented method was not up to the mark with respect to the productivity and efficiency metrics.

Elshaer et al. [30] presented a unique DC-DC architecture which allowed a PEV to use the grid for recharging the battery. Here, one rectifier and an advanced supportive resistance were utilized by the two modules. Combined function of the two modules reduced the overall size and complexity of the onboard circuitry. Although the transistor, auxiliary gate and regulator were costly, these also extended the converter's lifespan. But while the battery was being charged, the high voltage prevented it from operating in a better manner.

A novel combination of an onboard charge converter with the car and extra battery, was proposed by Nam et al. [31]. An integrated low-voltage direct current (LDC) converter was included in a conceptually encompassed converter. On the secondary side, an extra circuit consisting of a resistor, was used to control the variation across rectifiers and remove harmonics. But this design needed more equipment because some configurations required a lot of separate DC supplies.

Zinchenko et al. [32] suggested a one-stage remote charger, which did not require the need for a transitional DC-link. In this research, the converter designed for use over alternate current (AC) line voltage, was installed on a separate switching transistor. The adapter's performance features were what made it unique, while its continuous power recharging mode achieved an optimal efficiency. The suggested method removed the diode repossession features present in synchronous power converters to improve the efficiency. Unfortunately, the design of this converter necessitated use of an additional filter, which led to excessive output disruptions and poor transient adaptability.

Shahir et al. [33] demonstrated a novel transformer-less design for converters that reduced switch load in voltage management. This design was a good fit for greater-power, rapid-charging accumulator chargers for EV. The uninterrupted and interrupted current modes of the suggested converter were thoroughly analyzed in this study. The estimates were also provided for significant inductances and design factors related to the suggested controller. But when the diode delay was taken into account, the output impedance rose, in relation to the power that was preserved by the diode.

The comprehensive analysis demonstrates clearly that the benefits and adaptability of the power grid are greatly increased by the deployment of V2G. Since many EVs are used as two ESSs and load is used to support the mesh, a newly emerging technology known as V2G has evolved. Still, unorganized EV charging exhibits notable effects on the power system approach. Furthermore, this is a new and undeveloped form of technology. Many technological, economic and optimal coordination of the V2G system is required for its adoption. Moreover, the aspects pertaining to battery degradation are the current subjects that are also to be taken into consideration because EV charging and discharging coordination is relevant for optimization methods. Therefore, in this research, ANN and honey badger algorithm (HBA) controllers are introduced to balance the grids as well as the frequency, and this is clearly described in the following sections.

3.Methods

At present, continuous charging of EV faces challenges due to grid overload during daytime. Therefore, the best way to solve the emerging problem of grid-linked charging is through PV cells. The recommended approach provides EV charging with no delays, and works smoothly. The major advantage of the suggested approach is its punctual functioning that meets the entire EVs' charging requirements and also reduces additional load of the grid. Numerous optimization methods are utilized to construct the dominance algorithm. The weight values that link neurons in the neural network determine how effectively the network is functioning. Finding the ideal weight value is a challenging issue. For this reason, the biologically inspired HBA is employed. This algorithm finds the best answer based on the objective function by utilizing clever foraging strategies used by honey badgers and improving the rate of exploration. *Figure 1* illustrates the overall workflow of the suggested approach.

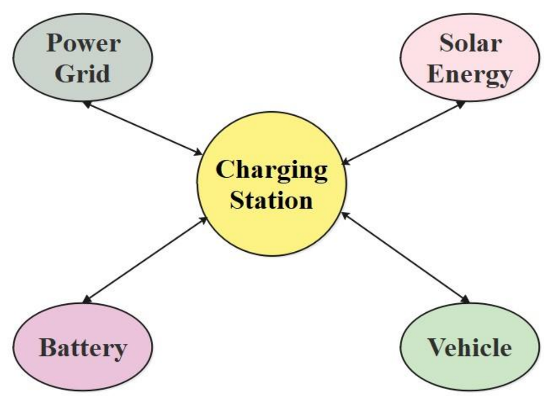


Figure 1 Entire workflow of suggested approach

3.1Energy management system (EMS)

The EMS effectively organizes EV charging using the collected data [34]. To optimize the operation of the smart grid, the EMS also collects distinctive EV profiles, wherein the EV profile is considered as $EV_{i,j}$ {struct}, i denotes charger group, while j denotes the chargers' outlet [35].

Figure 2 concludes the equilibrium process using $P_{grid} = P_{net} + P_{EV_M}$, where $P_{net} = P_L - P_{p_v}$. This equation represents the equilibrium between the generation and demand of electricity. *Figure 2* depicts the practical arrangement of the EMS block.

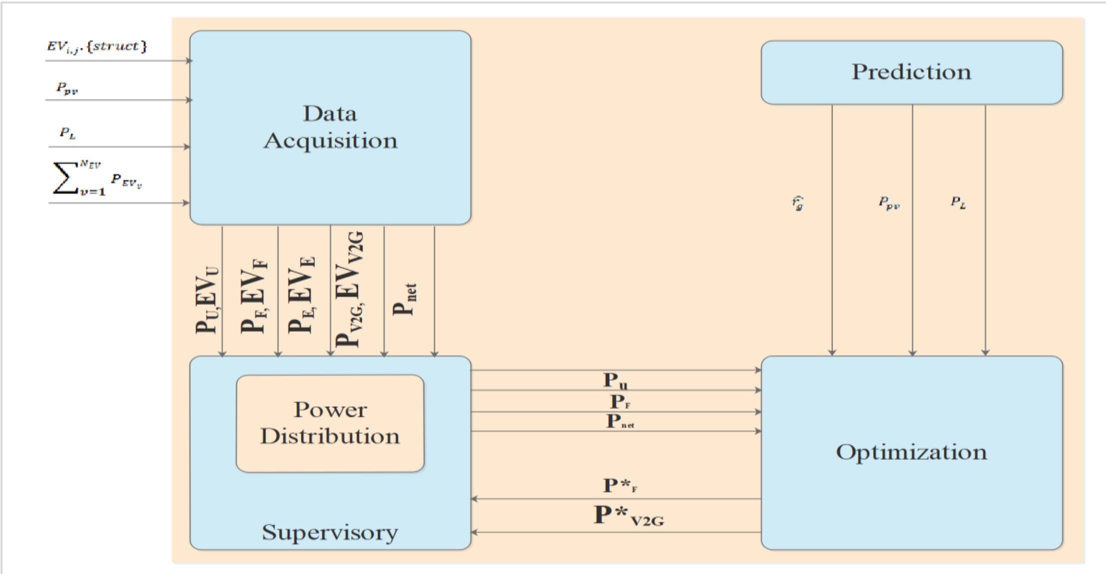


Figure 2 Outline of suggested model

3.2EMS functioning

The supervisor element oversees system-wide tasks that are performed real-time. The information derived from the data acquisition part is exploited [36]. The higher component updates the results to the inverter after each calculation step [37].

3.3EV Functional mode

The state of charge (SOC) behavior of each vehicle is ascertained by a battery, which is also usable for updating the inquiry [38]. The following Equation 1 contains the SOC:

$$SOC_v[n+1] = SOC_v[n] + \eta EV \frac{P_{EV_v}[n]\Delta t}{E_{bat_v}} \quad (1)$$

Depending on battery, the equation for each vehicle's SOC behavior is given below.
Wherein,

- The battery fraction of 1 sample gain for v is characterized as $SOC_v[n+1]$
- The SOC at sample n is shown by $SOC_v[n]$.
- The charging/discharging efficiency is shown by ηEV.
- The charging power is denoted by $P_{EV_v}[n]$.
- The overall battery capacity for vehicle v is denoted by E_{bat_v}. Equation 2 is thus expressed as follows:

$$0 \le SOC_v[n+1] \le 1 \quad (2)$$

While the control performance is restricted, Equation 3 is stated as:

$$PEV_v = \begin{cases} P_{EV_v}, & if\ 0 \le SOC_v[n+1] \le 1, \\ 0, & otherwise \end{cases} \quad (3)$$

The connection of EV incorporation [39] is expressed as Equation 4:

$$EV_{conn} = \begin{cases} 1, if\ EV_{i,j}.\{t_0\} \le EV_v(t_m) \le EV_{i,j}.\{t_f\}, \\ 1, if\ SOC_v[n+1] \le 1, \\ 0,\ otherwise \end{cases} \quad (4)$$

$\{EV_{i,j}.\{t_0\}$ and $\{EV_{i,j}.\{t_f\}$ are arguments of EV acquisition structure at initial and final charging instance. The current time in period $[t_i, t_f]$, is indicated by the parameter t_m. The rate of t_i is initially expressed in terms of t_0. The EV acquisition framework refers to $[t_i, t_f]$ as the start and ultimate charging times, respectively.

HBA's primary features are its use of randomness for setup, its two randomly chosen phases, and its cardioid motion during the exploration phase. There are various benefits including, hybridization that are combined with more conventional techniques for optimization. By combining the benefits and operators of various algorithms, the HBA method is improved further to find the optimal solution for prevailing issues. The many uses include, solving problem that is possible to be formulated as a function optimization problem. The proposed approach called HBA-ANN is an improvement over the recently developed HBA. Further, augmentation is achieved by incorporating the ANN's training and transfer functions. Both population variety, and the capacity to break free from local minimums, are enhanced by the HBA-ANN [40].

3.4Artificial neural network (ANN)

The ANN model consists of a set of weights, action functions and connections between nodes. In addition to this, there exists an input layer, an output layer, and one or more hidden layers [41]. When modeling issues, the ANN's effectiveness is greatly influenced by the number of hidden layers and the algorithm that is chosen. Feed-forward neural networks (FFNN) which are commonly utilized in the development of ANN, are the most regularly used neural networks for simulating and forecasting hydrological challenges [42]. Equation 5 represents how input X and output Y are related.

$$Y = f(W_1X_1 + W_2X_2 + \cdots W_nX_n + b) \quad (5)$$

Wherein f refers to the action function, b refers to bias, and W_i denotes the link weight [43].

3.5Honey badger algorithm

3.5.1General biology

The Indian subcontinent, semi-desert regions and rainforests, are home to HBA creatures [44, 45]. Honey badgers have always attacked larger predators because of their fearlessness and also the predators' inability to flee. The bird plays a part in setting up a mutually beneficial contact or connection between the two animals by guiding the badger to the swarm and using its long claws to assist it in uncovering the beehives. Therefore, both creatures gain from their cooperation and partake in rewards [46].

3.5.2Inspiration

The two ways this algorithm uses to find food, are by employing a honey guide mode or by smelling and digging. The HBA imitates this behavior. It follows the honey trail, depending on the bird's help to enable direct interaction between the honeyguide bird as well as hives of bees.

3.5.3Stages of HBA

This is a list of the steps involved in the HBA calculation. Equation 6 shows the population of likely outcomes:

$$Population\ of\ candidate\ solution = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1D} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2D} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & x_{n3} & \cdots & x_{nD} \end{bmatrix} \quad (6)$$

$$position\ of\ i^{th}\ honey\ badger\ x_i = [X_i^1,\quad X_i^2, \ldots\ldots \quad X_i^D$$

Step 1: Initialization phase

The population number N and position of the honey badgers are determined using Equation 7.

$$x_i = lb_i + r_1 \times (ub_i - lb_i) \quad (7)$$

Where r_1 is a random number between 0 and 1. The position of i^{th} honey badger is labeled as x_i, which represents one potential solution among a population of N candidates. The lower bound lb_i and upper bound ub_i specify the bounds of search zones for the location of the honey badger.

Step 2: Intensity

Intensity is associated with concentration strength of the prey and distance among the honey badgers. Then, there is a quick movement when the odour is powerful. Equation 8 shows the aim of fragrance strength denoted by I_i. r_2 is a random number between 0 and 1. The source strength is explained in Equation 9.

$$I_i = r_2 \times \frac{S}{4\pi d_i^2} \quad (8)$$

$$S = (x_i - x_{i+1})^2 \quad (9)$$

S is an acronym for source or concentration strength, which is related to the location of the prey. The quantity d_i stated in Equation 10, indicates the distance between prey and i^{th} HB.

$$d_i = x_{prey} - x_i \quad (10)$$

Step 3: Density factor is updated

As it is iiteratively updated, the α's value gradually drops over time. Equation 11 determines this declining factor which reduces the degree of randomization as more iterations are made.

$$\alpha = C \times exp\left(\frac{-t}{t_{max}}\right) \quad (11)$$

t_{max} is the maximum number of iterations. The constant denoted by C is ≥ 1.

Step 4: Steer clear of local best

A flag F in the suggested method, restricts the exploring path. The algorithm's capacity enables the agents to explore the search space more properly at its maximum, by changing the search direction, thereby increasing the likelihood of finding the outstanding solutions.

Step 5: Location update

As previously explained, the update of HBA location (x_{new}) consists of two independent steps: the digging phase and honey phase. In the digging phase, a honey badger makes motions resembling the shape of a cardioid. Equation 12 signifies the replicated motion.

$$x_{new} = x_{prey} + F \times \beta \times I \times x_{prey} + F \times r_3 \times \alpha \times d_i \times |cos(2\pi r_4) \times [1 - cos(2\pi r_5]| \quad (12)$$

In this case, x_{prey} denotes the prey's position that is closest to the best location that is found so far, or the global best location. The ability of the badger to obtain food is shown by the parameter $\beta \geq 1$. d_i refers to the distance between the badger and prey. The three distinct random numbers, r_3, r_4, and r_5, range from 0 to 1. Equation 13 that determines its value, is used to modify the search direction by the variable F, which functions as a flag.

$$F = \begin{cases} 1 & if\ r_6 \leq 0.5 \\ -1 & else, \end{cases} \quad r_6 \in 0 \text{ to } 1 \qquad (13)$$

A number of variables during the digging stage significantly influence the behavior of honey badgers. These consist of the time-varying component α and the prey's scent intensity denoted by I. Furthermore, the badger encounters F-designated disruptions while excavating, which enable it to choose an even more advantageous prey spot [47]. The location of prey is represented by the variable x_{prey}, whereas the honey badger's new position is represented by x_{new}. Equation 14 demonstrates that the badger finds its prey near to the place identified, and thus, accounting for the distance data d_i.

$$x_{new} = x_{prey} + F \times r7 \times \alpha \times d_i, r_7 \qquad (14)$$

The variable α measures how search habits are evolved. Disturbances that affect the honey badger are potentially classified as F. By including the training/transfer function from the ANN, the enhancement is accomplished and denoted as HBA-ANN.

4.Results

This study supports the experimental findings by building and evaluating the V2G-G2V assessment using MATLAB R2022b. Windows 11 OS and a mainframe Intel Core i7 with 16GB of random-access memory (RAM) are deployed. The following parameters are considered for evaluation: number of hidden layers=10, training function=Adam, integer=1000, population=300, learning rate=0.001, and epochs=1000. This paper outlines many approaches for charging EV throughout the day utilizing a smart-grid-based charging station. The recommended strategies facilitate the charging station's capacity to charge constantly. The findings show that EV charging with the combination and recommended method is continuous throughout the charging procedure. The Simulink representation of the entire study is shown in *Figure 3.*

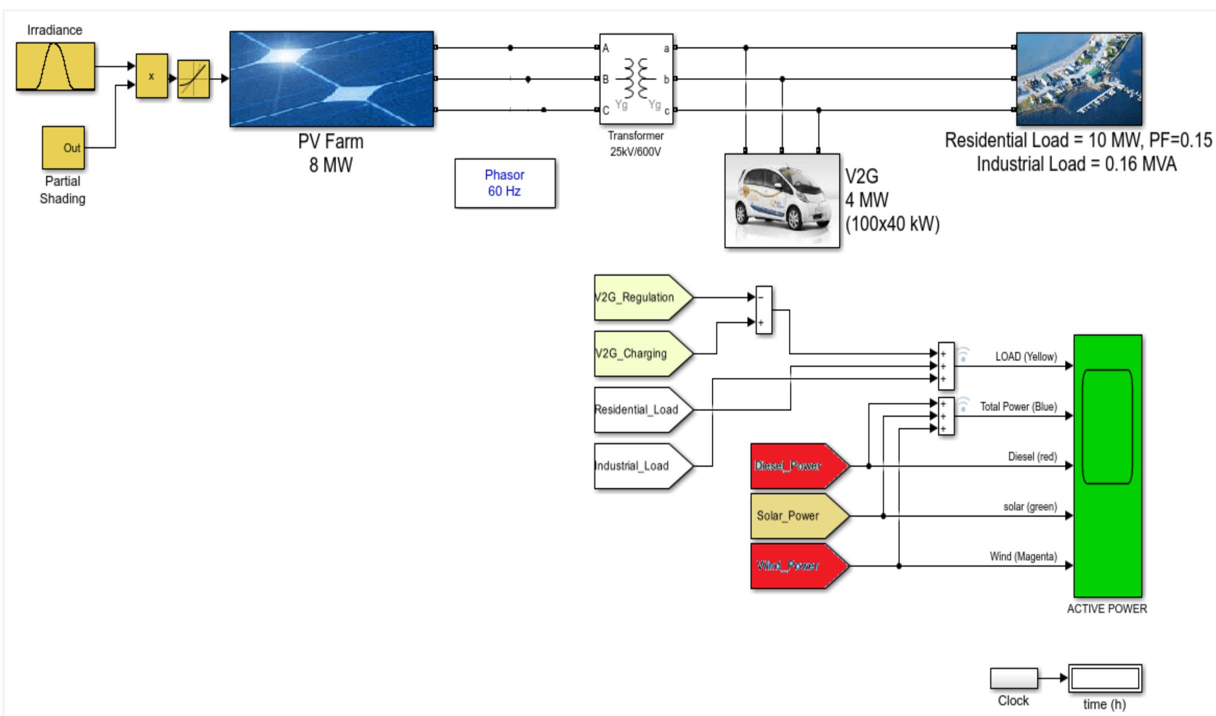


Figure 3 Simulation representation of a proposed method

In order to monitor the maximum power, maximum power point tracking (MPPT) is used to regulate the duty cycle and match the required load at maximum power. In order to push the PV to the peak MPPT level and produce a new duty cycle value, a converter is used to raise the voltage. Thus, variations in the MPPT value depend on the connected load. The MPPT precision and power performances are displayed in *Figure 4*. The outcomes unequivocally demonstrate that the proposed HBA-ANN attains a higher precision of 97.06%, outperforming more established methods such as African vulture optimization (AVO) with an ANN of 92.28% and Gorilla troops optimization (GTO) with an ANN of 94.79%.

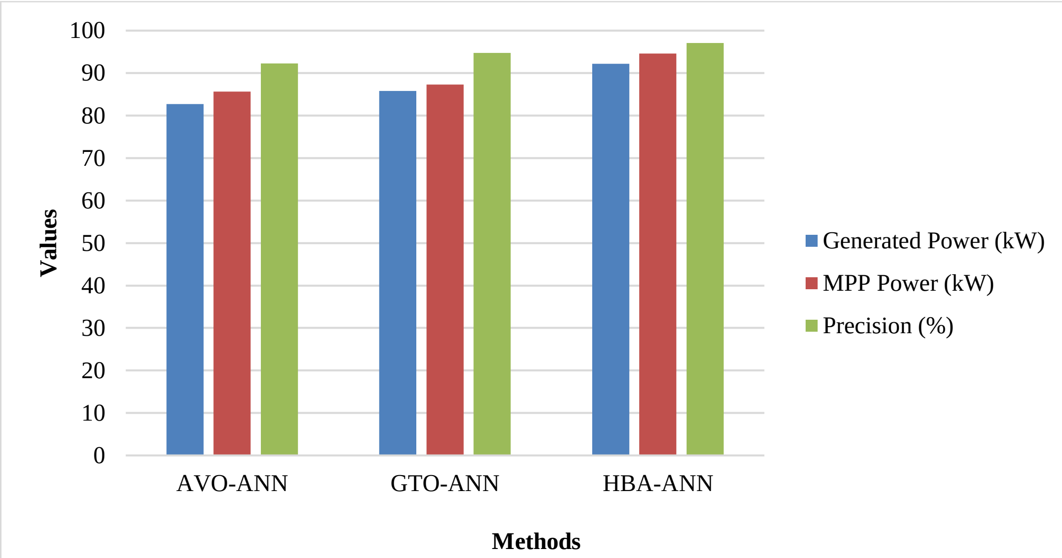


Figure 4 PV performance comparison using various optimization techniques

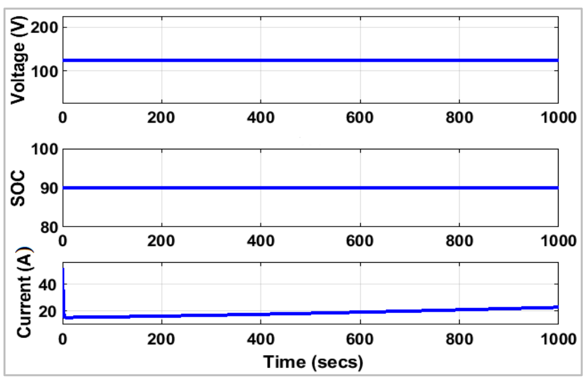


Figure 5 Electric vehicle performance in terms of voltage, SOC, and current

To make this arrangement better, voltage source inverter present in the system needs to have a variety of features. Ther EV performances are represented in *Figure 5*. The SOC protects the batteries from unforeseen disturbances and avoids overcharging them, which prevents the damage of their internal configuration.

Table 1 presents a comparison of several optimization schemes, along with the proposed HBA-ANN optimization scheme.

Furthermore, it properly identifies when the load has proper charging circumstances as well as low voltage characteristics. The comparison between EV, and conventional non-optimization techniques like differential evolution and simulated annealing, is presented in *Table 2*.

While retaining efficiency throughout the subsequent stage, the suggested charger setup provides an extraordinarily wide output voltage range. An internal parameter in the framework indicates each semiconductor device’s concurrent power dissipation. The values that indicate how much power a component uses over time, are computed using a logarithmic approach. This efficiency function ascertains the circuit's efficiency as it accounts for the losses of components, based on a specific power consumption.

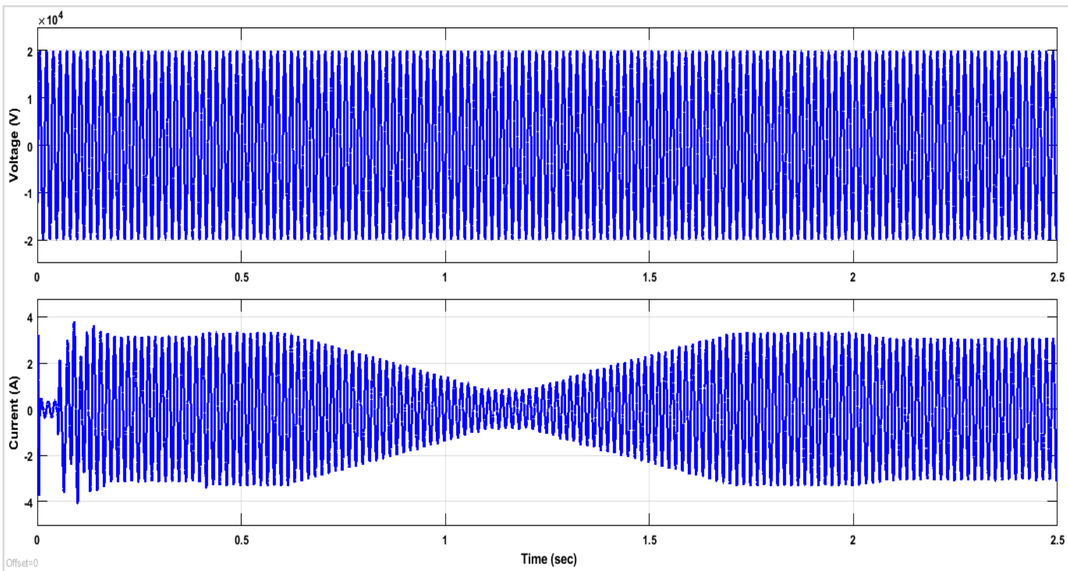
Table 1 Comparing the EV’s HBA-ANN performance with other various optimization techniques

Optimization methods	**THD (%)**	**Efficiency (%)**	**Power loss (KW)**
AVO-ANN	4.01	95.76	0.213
GTO-ANN	3.56	95.92	0.204
HBA-ANN	3.12	97.14	0.186

Table 2 Performance comparison of EV's HBA-ANN with traditional non-optimization methods

Optimization methods	THD (%)	Efficiency (%)	Power loss (KW)
Simulated Annealing	4.98	91.05	1.736
Differential Evolution	4.76	91.73	1.255
HBA-ANN	3.12	97.14	0.186

While *Figure 6(a)* describes the grid voltage and current restrictions, *Figure 6(b)* shows the grid characteristics in further detail. The device creates enormous amounts of energy by raising the grid current/voltage under various illumination conditions. In the beginning, MPPT selects MPP to employ a number of controllers. Additionally, how the estimated PV sources are used with the controller to manage peak loads is described. The resulting architecture is mostly made up of precise, detailed simulation outcomes of testing that is difficult but secure. The technique is used to track how PV modifies behavior in response to an active behavioral shift.



(a)

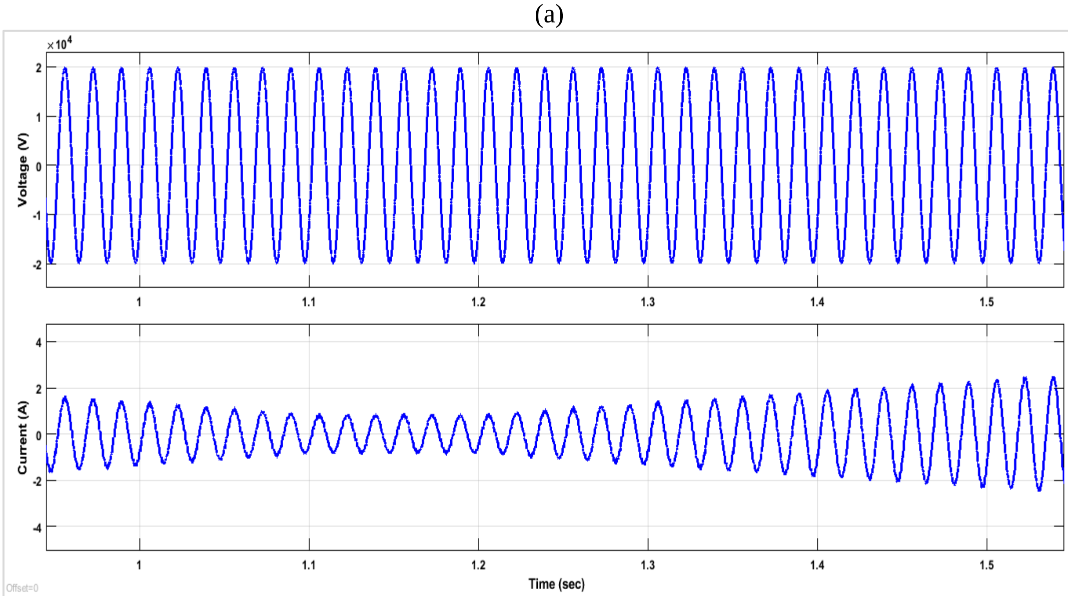


Figure 6 Zoom (a) View of the current and voltage (b) and Grid variables

4.1Comparative analysis

In the present research, the battery model is minor, inexpensive, and less complex than earlier battery chargers, so it does not need any new components. The proposed method's comparative analysis is displayed in *Table 3*. In *Table 3*, the proposed HBA-ANN is compared with ANN-PSO [21] and RI [24]. The existing ANN-PSO [21] attains an efficiency of 97%, while the existing RI controller [24] has 96.5% efficiency which are lesser outcomes when compared to the proposed HBA-ANN that achieves 97.14% efficiency. The THD evaluation for HBA-ANN is revealed in *Figure 7*.

Table 3 Comparative study of various performances

Performances	ANN-PSO [21]	RI [24]	HBA-ANN
Efficiency (%)	97	96.5	97.14
THD (%)	-	-	3.26

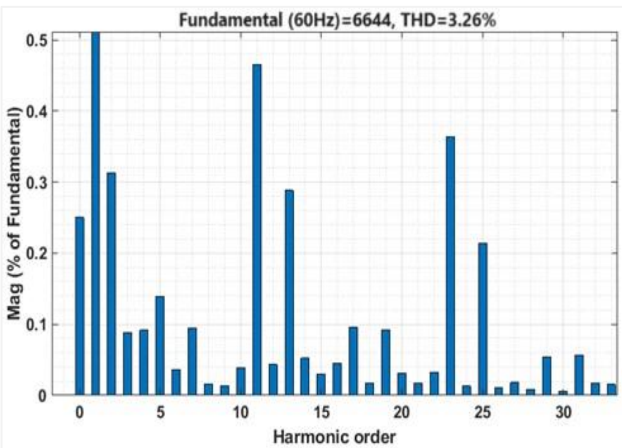


Figure 7 THD performance of HBA-ANN

5.Discussion

This study creates a hybrid intelligent model called HBA-ANN for balancing the power between various sources in terms of THD, efficiency, and it is compared with the existing ANN-PSO [21] and RI [24] methods. The result analysis clearly demonstrates that proposed HBA-ANN achieves an efficiency and THD of 97.14% and 3.26 respectively; while the existing ANN-PSO [21] and RI controller [24] gain efficiencies of 97% and 96.5% respectively. Similarly, in terms of precision, the proposed HBA-ANN achieves a higher precision of 97.06%, outperforming the existing methods AVO-ANN and GTO-ANN that have precisions of 92.28% and 94.79% respectively. When combined with EV charging, the two transformations have the potential to both impede and enhance one another. Firstly, the grid needs to supply drivers of EV with dependable, reasonably priced electricity and easy access to charging stations. Secondly, the grid's transformation is impacted by EV charging due to increased demand, accelerated equipment aging or upgrades, misalignment with renewable generation, or even the provision of grid services. In this work, that connection is addressed by figuring out what factors influence the demand for charging EV and how to modify it to minimize the effects on the electrical grid.

5.1Limitation

The ideal network structure for ANNs, is not determined exactly by the rulebook; instead, it is discovered via trial and error. Because the network reduces sample error to a certain extent in order to complete training, optimal results are not obtained during the training phase as expected. By utilizing the optimization techniques, ANNs are improvable and some of their drawbacks in selecting the optimal network structure are possible to be eliminated. In order to optimize neural networks, it is crucial to choose that optimization parameter of the neural network which produces the best results. Despite this, not every optimization technique offers the ideal answers to particular issues. Moreover, even when some optimization methods do function, more must be done to enhance their effectiveness. Because it is still very difficult to accelerate an algorithm's convergence, new optimization approaches inspired by nature must be developed on a regular basis to further progress the field of heuristic optimization. Installing solar panels on the roof or ground allows the harnessing of the sun's energy to create power that is used for charging electric cars or stored-in batteries, which may be analyzed with real-time data in the future. A complete list of abbreviations is listed in *Appendix I.*

6.Conclusion and future work

An EMS for PV installations, EV parking lots, and smart grid is built by this research's effort. The EMS is evaluated by HBA-ANN to achieve stability among the search spaces while evading unsuitable areas. HBA-ANN is tested against number of optimization techniques, including the AVO and GTO, taking into account the identical setup. The results of the article display how well the HBA works to solve issues with intricate search spaces. The investigation's findings show that the HBA-ANN controller outperforms the AVO and GTO controllers in terms of efficiency (97.14%), power loss (0.186kW), and THD (3.26%). To handle large-scale optimization challenges, future research may utilize binary and multi-objective characteristics in addition to chaotic maps. Furthermore, this research may be investigated with real-time values to check the cost and scalability of the implemented model.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
None.

Author's contribution statement
For this research work all authors' have equally contributed in Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

References

[1] Lutsenko I, Fedoriachenko S, Beshta OO, Vesela M, Koshelenko I. Estimation of the potential impact of electric vehicles on the distribution network's operation modes. Mechanics, Materials Science & Engineering. 2017.

[2] Jain F, Bhullar S. Operating modes of grid integrated PV-solar based electric vehicle charging system-a comprehensive review. E-Prime-Advances in Electrical Engineering, Electronics and Energy. 2024:100519.

[3] Kumari A, Trivedi M, Tanwar S, Sharma G, Sharma R. SV2G-ET: a secure vehicle-to-grid energy trading scheme using deep reinforcement learning. International Transactions on Electrical Energy Systems. 2022; 2022(1):9761157.

[4] Ahmadi SE, Kazemi-razi SM, Marzband M, Ikpehai A, Abusorrah A. Multi-objective stochastic techno-economic-environmental optimization of distribution networks with G2V and V2G systems. Electric Power Systems Research. 2023; 218:109195.

[5] Kumar BA, Jyothi B, Singh AR, Bajaj M, Rathore RS, Berhanu M. A novel strategy towards efficient and reliable electric vehicle charging for the realisation of a true sustainable transportation landscape. Scientific Reports. 2024; 14(1):3261.

[6] Anjaiah K, Dash PK, Bisoi R, Dhar S, Mishra SP. A new approach for active and reactive power management in renewable based hybrid microgrid considering storage devices. Applied Energy. 2024; 367:123429.

[7] Spanoudakis NI, Akasiadis C, Iatrakis G, Chalkiadakis G. Engineering IoT-based open MAS for large-scale V2G/G2V. Systems. 2023; 11(3):1-28.

[8] Sun Q, Xie H, Liu X, Niu F, Gan C. Multiport PV-assisted electric-drive-reconstructed bidirectional charger with G2V and V2G/V2L functions for SRM drive-based EV application. IEEE Journal of Emerging and Selected Topics in Power Electronics. 2023; 11(3):3398-408.

[9] Zheng Y, Xue X, Xi S, Xin W. Enhancing microgrid sustainability: dynamic management of renewable resources and plug-in hybrid electric vehicles. Journal of Cleaner Production. 2024; 450:141691.

[10] Shaheen HI, Rashed GI, Yang B, Yang J. Optimal electric vehicle charging and discharging scheduling using metaheuristic algorithms: V2G approach for cost reduction and grid support. Journal of Energy Storage. 2024; 90:111816.

[11] Visakh A, Selvan MP. Feasibility assessment of utilizing electric vehicles for energy arbitrage in smart grids considering battery degradation cost. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. 2022; 44(2):4664-78.

[12] Shakeel FM, Malik OP. Vehicle-to-grid technology in a micro-grid using DC fast charging architecture. In Canadian conference of electrical and computer engineering 2019 (pp. 1-4). IEEE.

[13] Makeen P, Ghali HA, Memon S, Duan F. Insightful electric vehicle utility grid aggregator methodology based on the G2V and V2G technologies in Egypt. Sustainability. 2023; 15(2):1-14.

[14] Ur RU. A robust vehicle to grid aggregation framework for electric vehicles charging cost minimization and for smart grid regulation. International Journal of Electrical Power & Energy Systems. 2022; 140:108090.

[15] İnci M, Savrun MM, Çelik Ö. Integrating electric vehicles as virtual power plants: a comprehensive review on vehicle-to-grid (V2G) concepts, interface topologies, marketing and future prospects. Journal of Energy Storage. 2022; 55:105579.

[16] Shakeel FM, Malik OP. ANFIS based energy management system for V2G integrated micro-grids. Electric Power Components and Systems. 2022; 50(11-12):584-99.

[17] Singirikonda S, Obulesu YP, Kannan R, Reddy KJ, Kumar GK, Alhakami W, et al. Adaptive control-based isolated bi-directional converter for G2V& V2G charging with integration of the renewable energy source. Energy Reports. 2022; 8:11416-28.

[18] Abuelrub A, Hamed F, Hedel J, Al-masri HM. Feasibility study for electric vehicle usage in a microgrid integrated with renewable energy. IEEE Transactions on Transportation Electrification. 2023; 9(3):4306-15.

[19] Oad A, Ahmad HG, Talpur MS, Zhao C, Pervez A. Green smart grid predictive analysis to integrate sustainable energy of emerging V2G in smart city technologies. Optik. 2023; 272:170146.

[20] Kashiri S, Siahbalaee J, Koochaki A. Stochastic management of electric vehicles in an intelligent parking lot in the presence of hydrogen storage system and renewable resources. International Journal of Hydrogen Energy. 2024; 50:1581-97.

[21] Nouri A, Lachheb A, El AL. Optimizing efficiency of vehicle-to-grid system with intelligent management and ANN-PSO algorithm for battery electric vehicles. Electric Power Systems Research. 2024; 226:109936.

[22] Cheng H, Wang Z, Yang S, Huang J, Ge X. An integrated SRM powertrain topology for plug-in hybrid

electric vehicles with multiple driving and onboard charging capabilities. IEEE Transactions on Transportation Electrification. 2020; 6(2):578-91.
[23] He T, Lu DD, Wu M, Yang Q, Li T, Liu Q. Four-quadrant operations of bidirectional chargers for electric vehicles in smart car parks: G2V, V2G, and V4G. Energies. 2020; 14(1):1-17.
[24] Kanimozhi G, Natrayan L, Angalaeswari S, Paramasivam P. An effective charger for plug-in hybrid electric vehicles (PHEV) with an enhanced PFC rectifier and ZVS-ZCS DC/DC high-frequency converter. Journal of Advanced Transportation. 2022; 2022(1):7840102.
[25] Justin F, Peter G, Stonier AA, Ganji V. Power quality improvement for vehicle-to-grid and grid-to-vehicle technology in a microgrid. International Transactions on Electrical Energy Systems. 2022; 2022(1):2409188.
[26] Alsharif A, Tan CW, Ayop R, Lau KY, Moh'd DA. A rule-based power management strategy for vehicle-to-grid system using antlion sizing optimization. Journal of Energy Storage. 2021; 41:102913.
[27] Heydari-doostabad H, O'donnell T. A wide-range high-voltage-gain bidirectional DC–DC converter for V2G and G2V hybrid EV charger. IEEE Transactions on Industrial Electronics. 2021; 69(5):4718-29.
[28] Gonzalez M, Asensio FJ, San MJI, Zamora I, Cortajarena JA, Oñederra O. Vehicle-to-grid charging control strategy aimed at minimizing harmonic disturbances. International Journal of Energy Research. 2021; 45(11):16478-88.
[29] Ramos LA, Van KRF, Mezaroba M, Batschauer AL. A control strategy to smooth power ripple of a single-stage bidirectional and isolated AC-DC converter for electric vehicles chargers. Electronics. 2022; 11(4):1-19.
[30] Elshaer M, Bell C, Hamid A, Wang J. DC–DC topology for interfacing a wireless power transfer system to an on-board conductive charger for plug-in electric vehicles. IEEE Transactions on Industry Applications. 2021; 57(6):5552-61.
[31] Nam VH, Tinh DV, Choi W. A novel hybrid LDC converter topology for the integrated on-board charger of electric vehicles. Energies. 2021; 14(12):1-18.
[32] Zinchenko D, Blinov A, Chub A, Vinnikov D, Verbytskyi I, Bayhan S. High-efficiency single-stage on-board charger for electrical vehicles. IEEE Transactions on Vehicular Technology. 2021; 70(12):12581-92.
[33] Shahir FM, Gheisarnejad M, Sadabadi MS, Khooban MH. A new off-board electrical vehicle battery charger: topology, analysis and design. Designs. 2021; 5(3):1-15.
[34] Mojumder MR, Ahmed AF, Hasanuzzaman M, Alamri B, Alsharef M. Electric vehicle-to-grid (V2G) technologies: impact on the power grid and battery. Sustainability. 2022; 14(21):1-15.
[35] Bot Y, Yousfi A, Allali A. Smart control of the bidirectional energy exchange of electric vehicles with the electrical network. International Journal of Advanced Studies in Computers, Science and Engineering. 2022; 11(12):29-35.
[36] Amir M, Zaheeruddin, Haque A, Kurukuru VB, Bakhsh FI, Ahmad A. Agent based online learning approach for power flow control of electric vehicle fast charging station integrated with smart microgrid. IET Renewable Power Generation. 2022.
[37] Gan W, Wen J, Yan M, Zhou Y, Yao W. Enhancing resilience with electric vehicles charging redispatching and vehicle-to-grid in traffic-electric networks. IEEE Transactions on Industry Applications. 2023; 60(1):953-65.
[38] Hanna B. Vehicle-to-grid and electric vehicle-integrated demand response management. In artificial intelligence applications in battery management systems and routing problems in electric vehicles 2023 (pp. 250-68). IGI Global.
[39] Manickam VK, Dhayalini K. Hybrid optimized control of bidirectional off-board electric vehicle battery charger integrated with vehicle-to-grid. Journal of Energy Storage. 2024; 86:111008.
[40] Zhou J, Wang D, Band SS, Mirzania E, Roshni T. Atmosphere air temperature forecasting using the honey badger optimization algorithm: on the warmest and coldest areas of the world. Engineering Applications of Computational Fluid Mechanics. 2023; 17(1):2174189.
[41] Sathyan S, Pandi VR, Antony A, Salkuti SR, Sreekumar P. ANN-based energy management system for PV-powered EV charging station with battery backup and vehicle to grid support. International Journal of Green Energy. 2024; 21(6):1279-94.
[42] Khan MA, Saleh AM, Waseem M, Sajjad IA. Artificial intelligence enabled demand response: prospects and challenges in smart grid environment. IEEE Access. 2022; 11:1477-505.
[43] Madichetty S, Banda MK, Banda SK. Implementation of deep learning based bi-directional DC-DC converter for V2V and V2G applications in microgrid-an experimental investigation. Energies. 2023; 16(22):7614.
[44] Hashim FA, Houssein EH, Hussain K, Mabrouk MS, Al-atabany W. Honey badger algorithm: new metaheuristic algorithm for solving optimization problems. Mathematics and Computers in Simulation. 2022; 192:84-110.
[45] Wang F, Bi S, Feng S, Zhang H. A novel honey badger algorithm with golden sinusoidal survival rate selection for solving optimal power flow problem. Electrical Engineering. 2024:1-9.
[46] Huang P, Zhou Y, Deng W, Zhao H, Luo Q, Wei Y. Orthogonal opposition-based learning honey badger algorithm with differential evolution for global optimization and engineering design problems. Alexandria Engineering Journal. 2024; 91:348-67.
[47] Diab AA, Tolba MA, El-rifaie AM, Denis KA. Photovoltaic parameter estimation using honey badger algorithm and African vulture optimization algorithm. Energy Reports. 2022; 8:384-93.

Abdul Khadar Asundi a received a B.E In Electrical and Electronics Engg. From UBDT College of Engg., Davangere, Karnataka, India. He holds an M.Tech., Degree in Electrical Power Systems from the National Institute of Engineering Mysore, Karnataka, India. Obtained a Ph.D. in Electrical Engineering Science from Visvesvaraya Technological University Belagavi, Karnataka, India. Currently, he is an Professor and Assistant HOD in the Department of Electrical and Electronics Engg., at BITM Ballari, Karnataka, India. He has published many papers in International journals and International conference proceedings and has one patent on an IOT-based Smart Energy Meter. At present, he is guiding five students in electrical power systems and smart grid at Visvesvaraya Technological University, Belagavi, and Karnataka, India. He has around 22 years of teaching and research experience.
Email: abdulkhadar@bitm.edu.in

Abdul Lateef Haroon Phulara Shaik received a B.E in Electronics and Communication Engineering RYMEC, Ballari, Karnataka, India. He holds an M.Tech., Degree in VLSI Design and Embedded Systems from K S School of Engineering and Management, Karnataka, India. Obtained a Ph.D. in Electrical Engineering Sciences from Visvesvaraya Technological University Belagavi, Karnataka, India. Currently, he is an Associate Professor in the Department of Electronics and Communication Engg., at BITM Ballari, Karnataka, India. He has published many papers in International and National journals and international conference proceedings and has three patents. At present, he is guiding four students at Visvesvaraya Technological University, Belagavi, and Karnataka, India. He has around 12 years of teaching and research experience.
Email: abdul.lh@bitm.edu.in

Syed Mohiuddin has completed his PhD in Fluid Dynamics from Gulbarga University, Gulbarga. Currently, he is an Associate Professor in the Department of Mathematics at Ballari Institute of Technology and Management, Ballari. He has published papers in International journals. At present he is guiding two students in Fluid Dynamics under Visvesvaraya Technological University, Belagavi, and Karnataka, India. He has around 23 years of teaching and research experience. His fields of interests in fluid dynamics include: Variable Viscosity, Variable Conductivity, Nano Fluid, Casson Fluid, Mixed Convection and Micro Polar Fluid.
Email: syedmohiuddin@bitm.edu.in

Naseeruddin is a member of Institution of Engineers (IE) India, received his PhD in Faculty of Electrical Engineering Sciences from Visvesvaraya Technological University, Karnataka. Currently he is working as an associate professor in the Department of Electronics and Communication Engineering, Ballari Institute of Technology and Management, Ballari, India. He has around 15 years of teaching and research experience. His fields of interests include: Wireless Mobile Adhoc Networks, Antenna Design, Robotics, Wireless Communication, Machine Learning in Wireless Networks, Embedded Systems and VLSI Low Power Design.
Email: naseeruddin@bitm.edu.in

Farzana Begum Kalburgi received a B.E In Electrical and Electronics Engg. From RYMEC College of Engg., Ballari, Karnataka, India. She holds an M.Tech., Degree in Power electronics from BITM Ballari, Karnataka, India. Currently, she is an Assistant Professor in the Department of Electrical and Electronics Engg., at BITM Ballari, Karnataka, India. She has one patent on an IOT-based Smart Energy Meter.
Email: kalburgishaikh@gmail.com

Appendix I

S. No.	Abbreviation	Description
1	AC	Alternate Current
2	AVO	African Vulture Optimization
3	ANN	Artificial Neural Network
4	DC	Direct Current
5	EV	Electric Vehicle
6	EMS	Energy Management System
7	ESS	Energy Storage Systems
8	FFNN	Feed-Forward Neural Networks
9	GTO	Gorilla Troops Optimization
10	G2V	Grid-To-Vehicle
11	HBA	honey badger algorithm
12	HBA-ANN	Honey Badger Algorithm and Artificial Neural Network
13	IEEE	Institute of Electrical and Electronics Engineers
14	LCL	Inductor-Capacitor-Inductor
15	LDC	Low-voltage Direct Current
16	MPPT	Maximum Power Point Tracking
17	MPC	Model Predictive Control
18	PSO	Particle Swarm Optimization
19	PV	Photovoltaic
20	PEV	Plug-In Electric Vehicles
21	PFC	Power Factor Correction
22	RAM	Random-Access Memory
23	RI	Resettable Integrator
24	RB-EMS	Rule-Based Energy Management Strategy
25	SOC	State of Charge
26	SRM	Switched Reluctance Motor
27	THD	Total Harmonic Distortion
28	V2G	Vehicle-To-Grid
29	ZCS	Zero Current Switching
30	ZVS	Zero Voltage Switching