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RESEARCH ARTICLE

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Management of electric vehicle charging stations in low-voltage distribution networks integrated with wind turbine–battery energy storage systems using metaheuristic optimization

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ABSTRACT

This study investigates the IEEE 69-bus distribution network with three wind turbines (WTs) connected at the same buses of three battery energy storage systems (BESSs), with three 20- or 30-outlet electric vehicle charging stations (EVCSs) for charging electric vehicles (EVs). The honey badger algorithm (HBA) is adopted to minimize daily energy loss. The HBA determines the best size and position for three WT-BESS buses and three EVCS buses. The HBA calculates BESS size and operation mode to minimize daily energy loss. The demand of EVCSs varies throughout the day depending on the random choice of the number and state of charge of EVs entering the station. This results in the active and reactive energy losses and utility input energy decreasing by 63.5%, 60.6% and 59.6%, respectively, and the minimum voltage increasing from 0.9256 to 0.9839 pu. The network voltage profile and stability are also improved.

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KEYWORDS
EVCS; BESS; energy losses; distribution networks; wind turbine generation

1. Introduction

Both fossil fuels and nuclear reactors, which have adverse environmental effects, are currently used to generate electric power. The production of greenhouse gases from fossil fuel-based generation is one of the significant environmental issues currently faced by the world. Although environmentally beneficial, the limited reliability of generation by renewable energy sources (RESs) hinders their broad usage (Jadhav, More, and Salkuti 2023; Salkuti 2022). Deploying storage devices is one option to compensate for a temporary loss of generation, but the initial cost and lack of longevity are problems. The use of electric vehicles (EVs) has expanded significantly, and scientists and academics are paying a lot of attention to this, although most of the global transportation sector relies on conventional energy sources (Urbina Coronado, Castañón, and Ahuett-Garza 2018; Moazami Goodarzi and Kazemi 2018; Eltamaly *et al.* 2017). In the transportation industry, EVs play a significant part in lowering carbon dioxide emissions (Salkuti 2021, 2023). EVs are three times more energy efficient and accessible to drive than internal combustion engine vehicles. They can also minimize exhaust emissions and pollutants. To serve the growing number of EVs more effectively, the infrastructure for charging EVs must be optimally planned. An efficient planning strategy will lower costs for network operators, and provide decision makers with information to make the right decisions on increasing the number of

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charging stations available to EV drivers (Zhang *et al.* 2021). However, the anticipated electric vehicle charging stations (EVCSs) will unavoidably put more strain on the current distribution network (DN).

To accommodate the growing number of EVs, the infrastructure for charging EVs must be planned with the utmost care. An efficient planning strategy would save costs for network operators, enable policymakers to make wise choices and increase the number of charging stations available to EV drivers. The existing DN would unavoidably experience more strain as a result of the anticipated EVCSs. Several publications have considered the simultaneous growth of both the DN and EVCSs (Jafarpour *et al.* 2022; Fathy and Abdelaziz 2020; Selvan and Swarup 2006). In a study by Hou *et al.* (2021), a capacity and location model for charging stations was suggested to consider both user and grid benefits. The model was solved using a Voronoi diagram and the particle swarm optimization (PSO) algorithm. The allocation of charging lots was proposed by Fathy and Abdelaziz (2020), using the competition over resource (COR) algorithm to improve system reliability and minimize the operation costs. Jafarpour *et al.* (2022) used Monte Carlo simulation for EV modelling to study the impact of vehicle-to-grid (V2G) strategies on the operation of the microgrid.

The optimal planning of EVCSs is receiving more attention. A multi-objective planning model was developed by Zhang *et al.* (2021) for the optimal allocation of EVCSs in DNs with wind power penetration. The study tried to minimize the cost of investment and energy losses while maximizing the total captured traffic flow. A new multi-stage expansion model was proposed, in which EVs were powered with renewable energy and storage systems. The EV model was based on travel patterns using a stochastic program. Shaaban *et al.* (2019) proposed a planning algorithm using the non-dominated sorting genetic algorithm-II (NSGA-II) for placing EVCSs in remote societies. The distributed generators (DGs) and EVCSs are jointly allocated and sized in the problem to balance the supply and the combined demand for loads and EVs. A coordinated planning model was proposed by Shao *et al.* (2021) for power DNs with fast EVCSs and batteries. The Gurobi/MATLAB® solver with a probabilistic model for EVs was adopted.

In many studies, the design of EVs discharging at EVCSs has depended on the use of probabilistic approaches. Ahmad, Khalid, and Panigrahi (2021) implemented a modified chicken swarm optimization (CSO) approach to locate the EVCSs in the DN in a way that provides the least amount of power loss without compromising other constraints. An innovative approach was presented by Alhasnawi *et al.* (2022) to position the solar-powered EVCS in the DNs with the lowest installation costs and smallest losses at different charging levels. The study formulation was considered as a stochastic issue, and PSO was used to carry it out in MATLAB. However, the power flow between the EVCS and the DN was not examined. Eid (2022) proposed a revolutionary two-level complete model to position the charging station with different objective functions.

The ant lion optimizer (ALO) algorithm has been used to size the EVCS and other devices to match the network system demand (Alsharif *et al.* 2021). The ALO algorithm minimizes the two different objectives of supply loss and cost of electricity while obtaining the most from renewables. An approach was suggested to manage the energy flow in the microgrid. However, the authors considered the EVCS with constant power demand. In addition to the battery energy storage system (BESS) and its scheduling, a sustainable approach was suggested by Pal, Bhattacharya, and Chakraborty (2021) to distribute public fast-charging locations and solar DGs. The EV assignment problem was solved using integer linear programming. The V2G optimization algorithm was used by Hashim *et al.* (2021) to maximize the charging and discharging power of each EV concerning the state of charge (SoC) of its battery while minimizing fluctuations in demand. The priority-based design principle served as the foundation for the optimization method. In a similar work (Gampa *et al.* 2020), fuzzy genetic optimization algorithm (GOA)-based approaches were developed for the best placement and sizing of DGs, supercapacitors and EVCSs to feed simultaneously the peak demand of the DN and the EV demand. The battery models were developed based on lithium-ion battery curves.

A summary of the previous work on the integration of EVCS with DNs is presented in Table 1. For each work, some details are reported about the solver, and the method of EV integration, with

Table 1. Comparison of approaches for the integration of electric vehicles (EVs) with distribution systems.

Reference	RES	BESS	EV demand modelling	Solver/algorithm	Benchmark
(Iqbal et al. 2022)	×	✓	Markov model	MCS	Single-bus MG
(Zhang et al. 2021)	Wind	×	Probabilistic model and SG	NAA	25, 54-bus RDS
(Hou et al. 2021)	×	×	Mathematical model	Voronoi diagram, PSO	Planning area
(Fathy and Abdelaziz 2020)	×	×	Mathematical model	COR	9, 33, 69-bus RDS
(De Quevedo, Munoz-Delgado, and Contreras 2019)	Wind, solar	✓	Historical data	CPLEX	54-bus RDS
(Shaaban et al. 2019)	Solar	×	Historical data	NSGA-II	38-bus RDS
(Shao et al. 2021)	Solar	✓	Probabilistic model and queuing theory	Gurobi/MATLAB	4 × 14-bus RDS
(Ahmad, Khalid, and Panigrahi 2021)	Solar	×	Stochastic approach	CSO	33-bus RDS
(Zeb et al. 2020)	Solar	×	Stochastic approach	PSO, OpenDSS	58-bus RDS
(Alsharif et al. 2021)	Wind, solar	✓	Constant power	ALO	2-bus MG
(Pal, Bhattacharya, and Chakraborty 2021)	Solar	✓	Mathematical model	HHO/GWO	33-bus RDS
(Hashim et al. 2021)	×	×	Priority-based scheduling	Mathematical modelling	Single-bus MG
(Gampa et al. 2020)	DG	×	Mathematical modelling	GOA	51, 69-bus RDS
Proposed	Wind	✓	Random distribution	HBA	69-bus RDS

Note: RES = renewable energy source; BESS = battery energy storage system; RDS = radial distribution system; DG = distributed generator; SG = scenario generation; MCS = Monte Carlo simulation; NAA = natural aggregation algorithm; PSO = particle swarm optimization; COR = competition over resource; NSGA-II = non-dominated sorting genetic algorithm-II; CSO = chicken swarm optimization; PSO = particle swarm optimization; DSS = distribution system simulator; ALO = ant lion optimizer; HHO = Harris hawks optimization; GWO = grey wolf optimizer; GOA = genetic optimization algorithm; HBA = honey badger algorithm.

either BESS and/or any RES, in the considered problem. Most EV demand modelling depends on mathematical formulations or probabilistic models and the adoption of historical data for modelling the demand for EVCSs. Most of these modelling methods are very exhaustive, needing various data sources to extract the behaviour of the EV demand, or are based on very complicated mathematical equations.

These methods share several characteristics of EV demand modelling, including the random distribution of EVs in the charging station and the randomness of their SoC at their initial connection to the charging outlets. This article considers these two characteristics of EVCS demand modelling by assuming a random number of EVs entering every charging station with a random SoC for every EV. At the same time, optimal sizing and allocation of the wind turbine (WT) generation with BESS are obtained by the new metaheuristic optimization honey badger algorithm (HBA). The HBA provides a robust and fast solution for the optimized problem. This work considers the operation and control of three EVCSs with the optimal operation of three WT-BESS units. The HBA minimizes the total energy loss of the DN while considering these load demands and power generations. The number of EVs per EVCS is assumed to lie between 50% and 100% of the maximum number of EVs to be charged by the EVCS. The basic contributions of this research can be outlined as follows.

- A new approach is adopted for EV distributions inside the EVCS with random initial SoC for every EV without using historical data or complicated mathematical modelling.
- Wind turbine generators (WTGs) and BESS units are effectively simulated and sized based on battery SoC and problem limitations.
- The newly published HBA optimizes the 69-bus DN with three WT-BESS units and three EVCSs to minimize the total daily energy loss.
- The study covers the stochastic network demand, optimal optimization of the BESS in charging/discharging modes and the EVCS variable demand during 24 h.

2. Objectives, constraints and adopted algorithm

The governing equations for the objective function and problem constraints of the adopted algorithm are explored in this section. The study's main objective is to minimize the daily energy loss of the DN being supported by WT power generation and loaded with an uncertain load of EVCSs, and variable demand throughout the day. The DN has three fixed EVCSs with a random number of EVs, and the EV stays connected in charging mode until its SoC reaches 100%. Every EVCS works independently of the other stations; consequently, the total EV demand is random. The three WT power generators are fixed in positions, and their output powers are assumed to follow a specific power profile decided by the WT data sheet.

The three BESS units are located on the same buses where the WT units are installed. The size of each BESS is optimized by the HBA according to the operating conditions over the 24 h of the day. A time step of 15 min is adopted in this study, which is believed to be suitable for the nature of WT and BESS operations. Besides the objective function, other performance parameters are recorded during the simulation phase.

2.1. Objective function

When a DG, such as a WT power generator or a BESS, is connected to a DN, the network performance is improved in terms of lower power losses, higher stability or an increasing voltage profile. In this study, the objective is to reduce the daily energy losses of the IEEE 69-bus network. Decreasing the network losses will, in turn, increase the bus voltages and stability. The power loss of any branch of the DN is calculated from (Eid *et al.* 2022):

$$P_{ch} = I_{ch}^2 \times R_{ch} \tag{1}$$

where P_{ch} is the branch loss; R_{ch} is the branch resistance per phase; and I_{ch} is the magnitude of the branch current per phase. The total of branch losses, P_{Loss}, is the summation of all individual branch losses:

$$P_{Loss} = \sum_{i=1}^{N_{ch}} P_{ch,i} \tag{2}$$

where N_{ch} is the number of branches of the DN. Energy loss during successive time steps is estimated from the trapezoidal rule, as:

$$E_{\Delta t,i} = \Delta t \times \left(\frac{P_{Loss,i} + P_{Loss,i+1}}{2} \right) \tag{3}$$

$$\Delta t = (t_{i+1} - t_i) = 15min \tag{4}$$

where $P_{Loss,i}, P_{Loss,i+1}$ are the total losses at the time steps of t_i, t_{i+1}. The total energy loss per day (E_{Loss}) is calculated as the summation of all energies of each time step:

$$E_{Loss} = \sum_{i=1}^{N_{ss}} E_{\Delta t,i} \tag{5}$$

where N_{ss} is the total time steps (96 steps of 15 min) over the hours of the day. The objective function for minimizing the total energy loss is expressed as:

$$f_{obj} = \min(E_{Loss}) \tag{6}$$

2.2. Performance parameters

Some indicative parameters are derived and recorded to thoroughly assess the performance of the DN while optimizing the size of WTGs and BESSs as well as the EV demand. These indicators represent the active/reactive power losses during the day to determine periods of small and large losses, total voltage deviations during the day showing the deviations of the absolute per-unit voltages from unity, and the extreme voltages during the day.

The extreme voltage values for the considered period are collected from the matching data for each time step of the calculation:

$$V_{min}^{G} = \min(V_{min}^{i}), i = 1 : N_{ss} \tag{7}$$

$$V_{max}^{G} = \max(V_{max}^{i}), i = 1 : N_{ss} \tag{8}$$

where $V_{\min}^{G}$ and $V_{\max}^{G}$ are the daily minimum and maximum voltage values calculated from $V_{\min}^{i}$ and $V_{\max}^{i}$ at the ith time step; and N_{ss} is the number of simulation steps ($= 96$). The same definition applies to the worst total voltage deviation (TVD) of the day:

$$TVD_{max}^{G} = \max(TVD_{max}^{i}), i = 1 : N_{ss} \tag{9}$$

where the TVD is calculated at any time step as:

$$TVD = \sum_{i=1}^{N_B} ||V_i| - 1| \tag{10}$$

where N_B is the network buses; and V_i is the ith bus voltage. The stability index (SI) is calculated as (Eid *et al.* 2020):

$$SI = 1 - [2(P_i R_{ki} + Q_i X_{ki}) - V_k^2]^2 - 4S_i^2 Z_{ki}^2 \tag{11}$$

where P_i, Q_i and P_i are the active, reactive and apparent power at the ith receiving end of any branch connected between k, i buses; R_{ki}, X_{ki} and Z_{ki} are the branch resistance, reactance and impedance; and V_k is the voltage at sending bus k.

2.3. Problem constraints

This subsection explores the constraints imposed on the problem to reduce the objective of the DN when integrated with WT power generation and EVCS variable demand. The number of charging EVs in every EVCS lies between the extreme limits:

$$\frac{N_{chg}}{2} \leq N_{EV} \leq N_{chg} \tag{12}$$

where N_{chg} and N_{EV} are the number of EV charging outlets inside every EVCS and the number of charging EVs, respectively.

Integrating RES or EVCS demand should not violate the allowable voltage limits (0.95–1.05 pu). If the voltage at any iteration lies outside the specified limits, the HBA will bypass it. Hence, the voltage must satisfy

$$V_{\min} \leq V_i \leq V_{\max} \tag{13}$$

where V_i is the voltage, which lies between the minimum acceptable voltage $V_{\min}$ and the maximum value of $V_{\max}$.

The BESS units work in either charging or discharging mode, depending on the network's status and their SoC. When the BESS works in charging mode, it is considered a load demand imposed on the DN, while in discharging mode, it will deliver power to the DN. In both cases, the BESS power should be within preset levels:

$$-P_{BESS}^{\min} \le P_{BESS}(t) \le P_{BESS}^{\max} \tag{14}$$

where $P_{BESS}^{\min} P_{BESS}^{\max} P_{BESS}^{\min} P_{BESS}^{\max}$ and P_{BESS} are the BESS minimum, maximum, and power at any time (t) during the simulation. In charging/discharging mode, the SoC should be within limits:

$$SoC_{BESS}^{\min} \le SoC_{BESS}(t) \le SoC_{BESS}^{\max} \tag{15}$$

where $SoC_{BESS}^{\min}$ and $SoC_{BESS}^{\max}$ are the allowable extremes of SoC of the BESS units.

The size of the WT power generation is taken from the optimal allocation of WT units, with the base case of the DN without EVCS demand. At any time, the power injected into the DN does not exceed the demand of the network.

$$\sum_{i=1}^{3} P_{WT,i} + \sum_{i=1}^{3} P_{BESS,i} \le P_{bd} \tag{16}$$

where $P_{WT,i}$ is the WT power generation of the ith unit; $P_{BESS,i}$ is the BESS power of the ith unit; and P_{bd} is the base network demand. At any iterative step, the load flow equations are satisfied at any bus of the DN:

$$P_i = \sum_{j=1}^{N_B} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i - \delta_j), i = 2 : N_B \tag{17}$$

$$Q_i = \sum_{j=1}^{N_B} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i - \delta_j), i = 2 : N_B \tag{18}$$

where P_i and Q_i are the injected real and reactive powers at bus i; V_i, V_j are the voltage magnitudes at buses i, j; δ_i, δ_j are their respective angles; and Y_{ij} is the branch admittance and its angle θ_{ij}.

2.4. Honey badger algorithm

The HBA is a new metaheuristic optimization algorithm (Hashim *et al.* 2022). The deriving equations, limitations and uses of the algorithm are explored in Hashim *et al.* (2022). The HBA is adopted in this study to optimize a DN supported with WT-BESS and loaded with EVCS units.

3. Method of analysis

This section presents the mathematical modelling of the main components used in the study, including the EVCS, WT and BESS.

3.1. EVCS modelling

The random number of EVs entering a charging station at a time, t, is given as:

$$N_{EV,i} = randi\left(\frac{N_{chg}}{2}, N_{chg}\right), i = 1 : 3 \tag{19}$$

where $N_{EV,i}$ is the number of charging EVs at the ith EVCS; N_{chg} is the maximum number of EV charging outlets of each station; and *randi* is a pseudo-random integer from a uniform discrete distribution.

The SoC of the kth EV is assumed to be random:

$$SoC_k = SoC_{\min} + (SoC_{\max} - SoC_{\min}) \times \; rand(N_{EV,i}), k = 1 : N_{st,i}, i = 1 : 3 \tag{20}$$

where $SoC_{\min}$ and $SoC_{\max}$ are the extreme SoC values of the EV's battery; *rand* is a random function; and $N_{st,i}$ is the total number of EVs charging at the ith station. The successive SoC for every EV is calculated based on the constant power demand of the vehicle of 25 kW. Thus, for every time step Δt of 15 min, the SoC increases by:

$$\Delta SoC = \frac{P_{EV} \times \; \Delta t}{\eta_{con} \times C_{EV}} \tag{21}$$

where P_{EV} is the rated power (kW) of the EV battery; C_{EV} is the capacity (kWh) of the EV battery; Δt is the time step of 0.25 h (= 15 min); and η_{con} is the efficiency of the battery converter. The SoC of every EV battery at any time step is calculated as:

$$SoC(t) = SoC(t - \Delta t) + \Delta SoC \tag{22}$$

The EV is assumed to charge under a constant power condition of 25 kW. Consequently, the change in SoC is constant; hence, the SoC of EV batteries increases linearly with time until it reaches total capacity, and also decreases linearly. When the EV is charging, it is considered as a load of 25 kW, whereas when the SoC reaches 100%, it is regarded as zero power demand. In this case, the total demand for the EVCS is calculated as the sum of power values of all charging EVs in this charging station, as:

$$P_{EVCS} = \sum_{k=1}^{N_{st}} P_k \tag{23}$$

The three stations are then added to the DN demand at their respective buses, and the DN is solved by the forward–backward sweep method (FBSM).

The integration of the EVCS into DNs depends on the availability of space and cable routes around a certain bus bar. Other technical points include the effect of the EVCS demand on the operation of the DN. It is known that the EVCS is a load added to the total demand of the DN that may increase the losses if it is not correctly connected at an optimal place. In this study, the HBA finds the best sites for the three EVCSs at buses 28, 36 and 47, such that the lowest possible loss is achieved after integrating them into the 69-bus DN. The worst case of connecting EVs to all station outlets is assumed while determining the optimal locations of the EVCSs.

3.2. WT modelling

The power of a WT is primarily affected by three factors: the wind speed distribution of the site, the hub height of the wind tower and the power output characteristic curve of the WT. The cube of wind speed, v, determines the WT generated power (Nadjemi *et al.* 2017):

$$P_{WT} = 0.5 \times \rho \times A \times C_p(\beta, \lambda) \times v^3 \tag{24}$$

$$\lambda = \omega_r \times R_r / v \tag{25}$$

The WT generated power at any time is given by:

$$P_{WT}(t) = \begin{cases} 0, & v(t) \; \langle v_{ci} or v(t) \rangle \; v_{co} \\ P_{WT} \times \frac{v(t) - v_{ci}}{v_r - v_{ci}}, & v_{ci} \le v(t) \le v_r \\ P_{WT} & v_r \le v(t) \le v_{co} \end{cases} \tag{26}$$

where v_{ci}, v_{co} and v_r represent predefined speed values; and P_{WT} is the generated power at rated speed. If $v < v_{ci}$ or $v > v_{co}$, the WT will turn off.

3.3. BESS modelling

To transform the direct current (DC) electricity from a BESS into alternating current (AC), a converter is required. The converter may run in all possible quadrants. As a result, the BESS can be viewed as either a load that consumes power during charging or a source that supplies power during discharging. When coupled to WT modules, the BESS converts the previously non-dispatchable WT into a dispatchable source. The BESS energy at bus k is stated in discharging mode ($P_{BESS}(t) < 0$) (Chen, Gooi, and Wang 2012; Kucevic *et al.* 2020) as:

$$E_{BESS}^{k}(t) = E_{BESS}^{k}(t-1) - \Delta t \times P_{BESS}^{k,D} \times \eta_d \tag{27}$$

where E_{BESS}^{k} is the energy at the kth bus; $P_{BESS}^{k,D}$ is the corresponding BESS discharging power; η_d is the efficiency; and Δt is the time step. For charging mode ($P_{BESS}(t) \geq 0$), the energy stored is (Chen, Gooi, and Wang 2012):

$$E_{BESS}^{k}(t) = E_{BESS}^{k}(t-1) - \Delta t \times P_{BESS}^{k,C} \times \eta_c \tag{28}$$

where $P_{BESS}^{k,C}$ is the corresponding BESS charging power; and η_c is charging efficiency. However, the energy stored at the kth bus lies between certain limits:

$$E_{BESS}^{k,\min} \leq E_{BESS}^{k}(t) \leq E_{BESS}^{k,\max} \tag{29}$$

In this work, 20% and 85% are taken as the limits (Chen, Gooi, and Wang 2012). The SoC of the battery at the kth bus is calculated as (Nadjemi *et al.* 2017; Radosavljević 2021):

$$SoC^{k}(t+1) = SoC^{k}(t) + \Delta SoC^{k} \tag{30}$$

$$\Delta SoC^{k} = \begin{cases} \frac{P_{BESS} \times \Delta t \times \eta_d}{C_{BESS}}, & P_{BESS} < 0 \\ 0, & P_{BESS} = 0 \\ \frac{P_{BESS} \times \Delta t}{C_{BESS} \times \eta_c}, & P_{BESS} > 0 \end{cases} \tag{31}$$

where P_{BESS} is the BESS power; Δt is 0.25 h (= 15 min); and C_{BESS} is the BESS rated capacity (kWh).

4. Simulations

The 69-bus radial DN (Rastgou, Moshtagh, and Bahramara 2018), as shown in Figure 1, is used as a test network provided with the studied renewables. The three BESSs are optimally allocated at bus numbers 11, 18 and 61, with variable sizes determined every time step Δt of 15 min by the HBA according to the load profile and the EVCS load. Moreover, the HBA optimally locates the EVCSs on buses 28, 36 and 47. The three optimal WT locations are the same as those of the BESS, to enable small cable connections and easy maintenance. A BESS enables utility providers to gather extra electricity generated from renewable sources and store it for periods when the utility needs it. The number of EVs charging simultaneously is random, between half and the total number of outlets. The EV fleet is assumed to enter the EVCS every 4 h as the average time needed to charge the vehicle. Thus, the total load of the EVs is random. The study includes the optimal operation of the network with renewables and BESSs during the 24 h of the day. Two case studies are considered here, according to the maximum number of charging outlets available in the EVCS:

- case study I: 20 EV chargers/station
- case study II: 30 EV chargers/station.

The 69-bus DN is simulated in both case studies with the installed WT and BESS resources. The WT energy is extracted from the daily wind profile shown in Figure 2. At the same time, the HBA

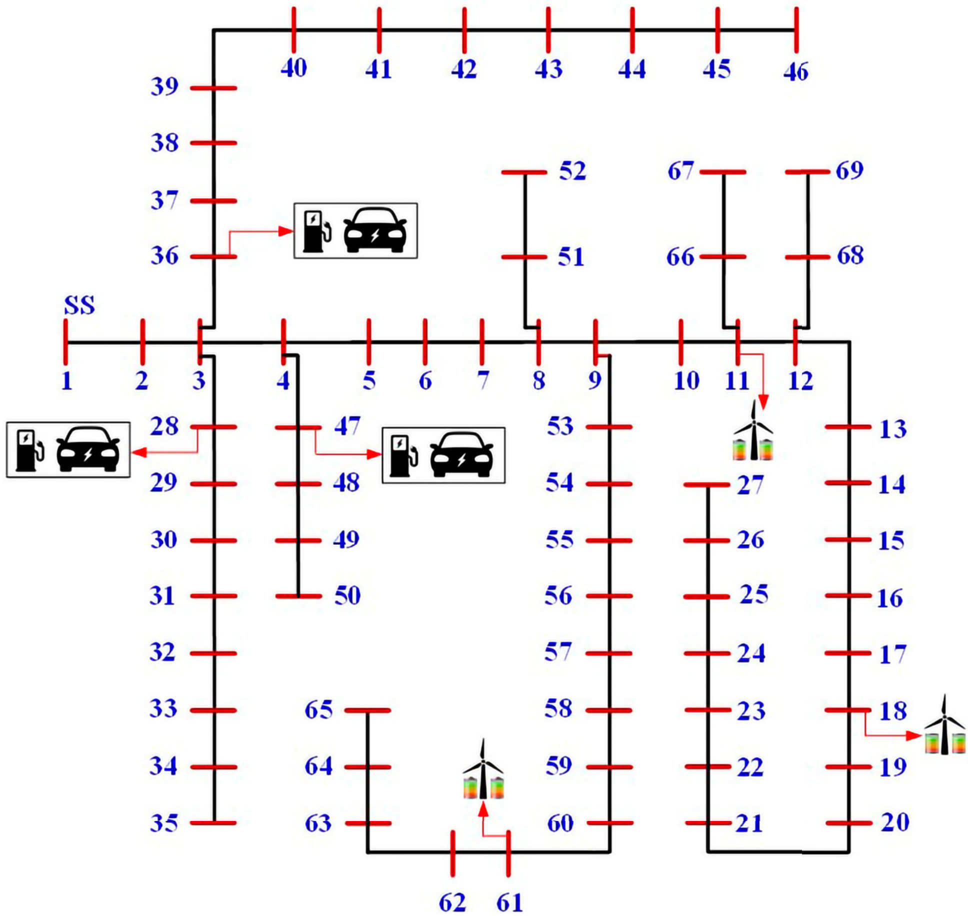

Figure 1. Single-line diagram of the 69-bus system with wind turbine, battery energy storage system and electric vehicle charging station units.

optimizes the BESS to work in charging or discharging modes depending on the operating conditions, network constraints and daily load curve (DLC), as shown in Figure 2.

The details of the proposed method to control the EVCS with renewable energies are shown in the flowchart of Figure 3. The locations of the EVCS and WT are found by the HBA to reduce the total network losses. Before entering the main loop, the required data and daily profiles of the WT and demand are collected. Moreover, each EVCS is assumed to have a random number of EVs charging at the start of the simulation, with random SoC. In the inner loop, the HBA optimizes the BESS sizes to minimize the network's losses. The FBSM load flow solves the DN while satisfying the network and problem constraints with every iteration. The process repeats 100 times, the maximum allowable number of iterations. When vehicles reach the maximum charging time of 4 h, a new fleet of EVs is allowed to enter the stations. The new fleet of every EVCS has a random number of EVs, with random SoCs. The old fleet left the EVCS with an SoC of 100%. The process repeats every 4 h until the whole day has ended. When the SoC of any EV reaches 100%, it is assumed to be disconnected from its outlet. As seen in Figure 4, every 4 h a new group of EVs joins the EVCS.

4.1. Case study I

In this case study, the EVCS has 20 EV charging outlets available in the station for possible connections. Thus, the total number of available chargers for the three stations is 60. The EV works only in

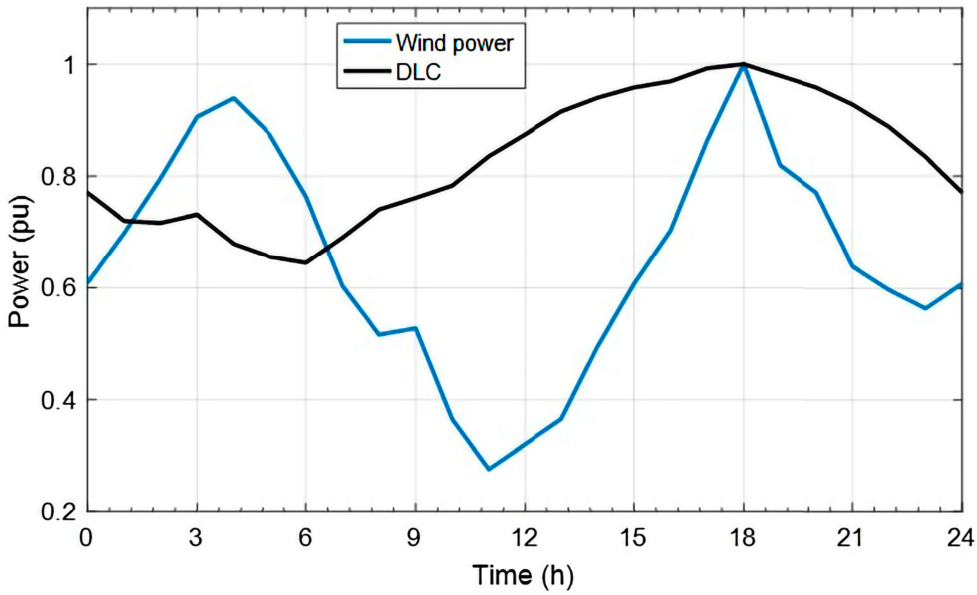

Figure 2. Profiles of wind power and system load. DLC = daily load curve.

grid-to-vehicle (G2V) mode; it is a load added to the system demand. In contrast, the three WTGs with the BESS units are optimized to provide minimum daily energy losses. The WTGs are located and sized by the HBA while satisfying the network constraints. At every EVCS, a random number of EVs charges for 4 h according to their initial SoC. The random number of EVs per station lies between 10 and 20. The number of EVs in each station varies between each run of the code. The EV charges at a constant power of 25 kW. The performance parameters of the system, including the active and reactive power losses, TVD and SI, are recorded during the simulation period of 24 h. The number of charging vehicles and their load are also outlined. For a selected run and given operating conditions, the random charging EVs in every EVCS are listed in Table 2 according to the time period during the day. The EV charges fully in 4 h; hence, every 4 h, all EVCSs are refreshed with new EV sets. According to its initial SoC, the EV remains in the EVCS until it reaches an SoC of 100%. When the SoC reaches 100%, the EV leaves the station.

The total load of the three EVCSs depends on the number of EVs connected to the charging outlets in every station. As the connected EVs are random, the total load per station varies, as shown in Figure 5. In the first period ($0.0 \leq t < 4.0$) of the day, 12 EVs will enter $EVCS_1$ and start charging with a total power of 300 kW, considering 25 kW/EV; 11 EVs start charging with a total demand of 275 kW in $EVCS_2$, and 16 EVs start charging in $EVCS_3$ with a total demand of 400 kW. According to their random initial SoC, these EVs will share the demand until reaching their entire SoC. The EV charges with constant power mode, and whenever the SoC of an EV reaches 100%, the EV leaves the station. Thus, the demand for EVCSs decreases with time, and by the end of the first period, all EVs are fully charged. In the second period ($4.0 \leq t < 8.0$) of the day, a new set of EVs enters the three EVCSs, and starts charging. The process repeats every 4 h. The corresponding SoC statuses of all EVs in $EVCS_1$, $EVCS_2$ and $EVCS_3$ are shown in Figure 6. Radar charts are used to show the density distribution of EVs during every period of the day. The randomness of the EVs per period and from station to station can be seen upon close inspection of the figure.

The HBA optimizes the three BESS units to minimize the network energy loss by minimizing the network loss in every simulation step. When the network demand increases as a result of EV charging or changes in the network demand, the BESS units discharge to cover the excess demand. In this case,

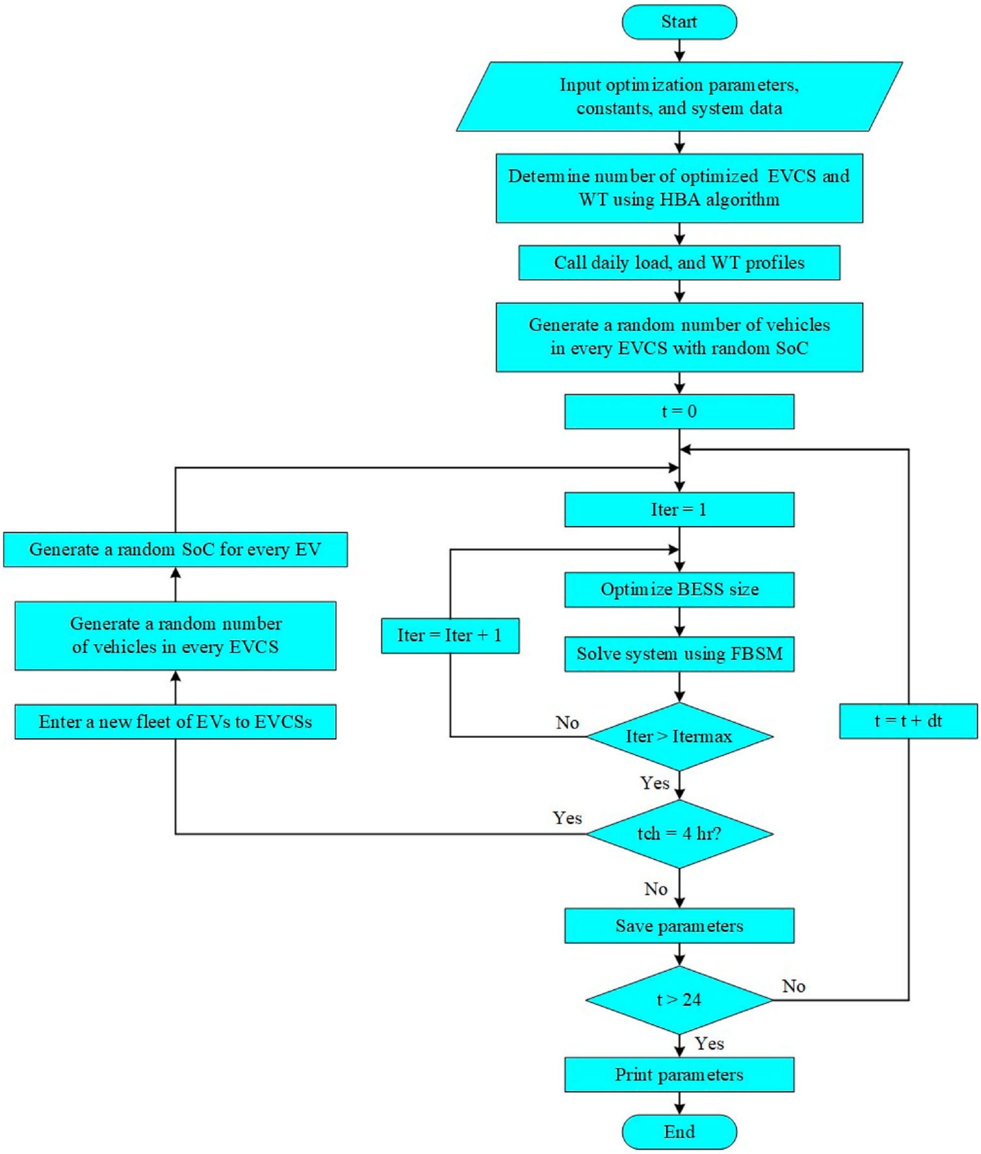

Figure 3. Flowchart of the proposed solution. EVCS = electric vehicle charging station; WT = wind turbine; HBA = honey badger algorithm; SoC = state of charge; EV = electric vehicle; BESS = battery energy storage system; FBSM = forward–backward sweep method.

the SoC of the BESS unit decreases according to the discharged power. In contrast, the SoC of the BESS increases when it charges with light load conditions. As the network load varies with variable EV load, the SoC of the BESS unit is expected to vary, as shown in Figure 7. The BESS units are located on the same buses as the WTs to take advantage of shorter connection cables and to provide an easy charging tool when the network demand is low. The maximum WT power is almost the same at buses 11 and 18, while at bus 61, a higher WT is installed. The considerable WTG power at bus 61 charges $BESS_3$ most of the time. When the SoC reaches the lower or upper limit of 0.2 or 0.85, respectively, the BESS stops the discharging/charging process.

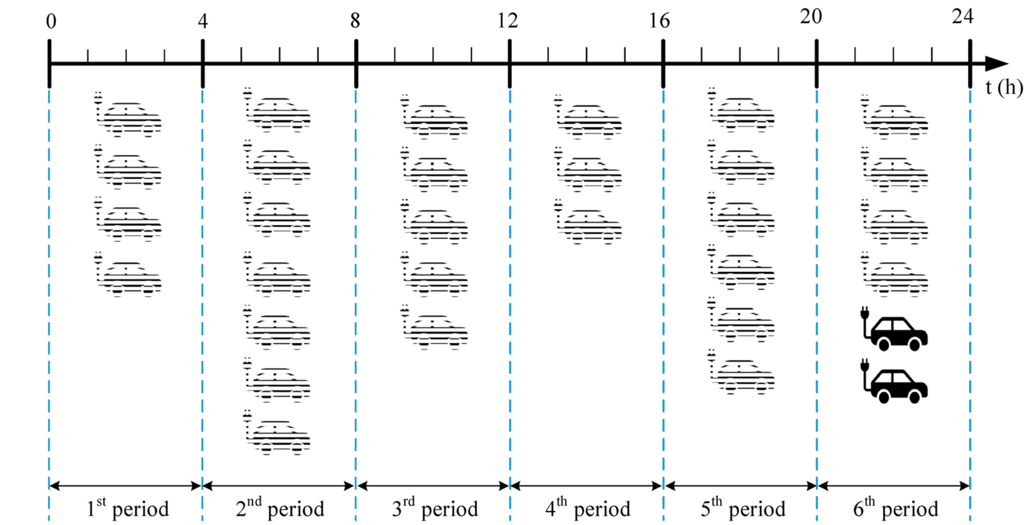

Figure 4. Representation of random electric vehicle batches entering the electric vehicle charging station every 4 h.

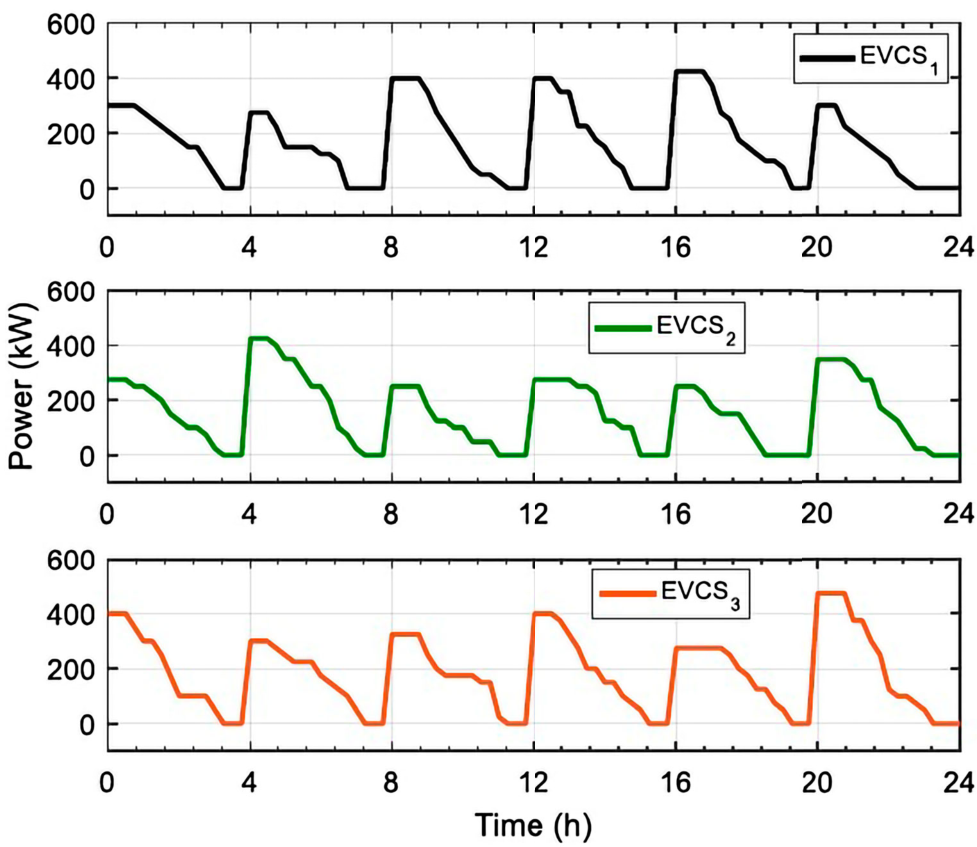

Figure 5. Total demand of the electric vehicle charging stations (EVCSs) for case study I.

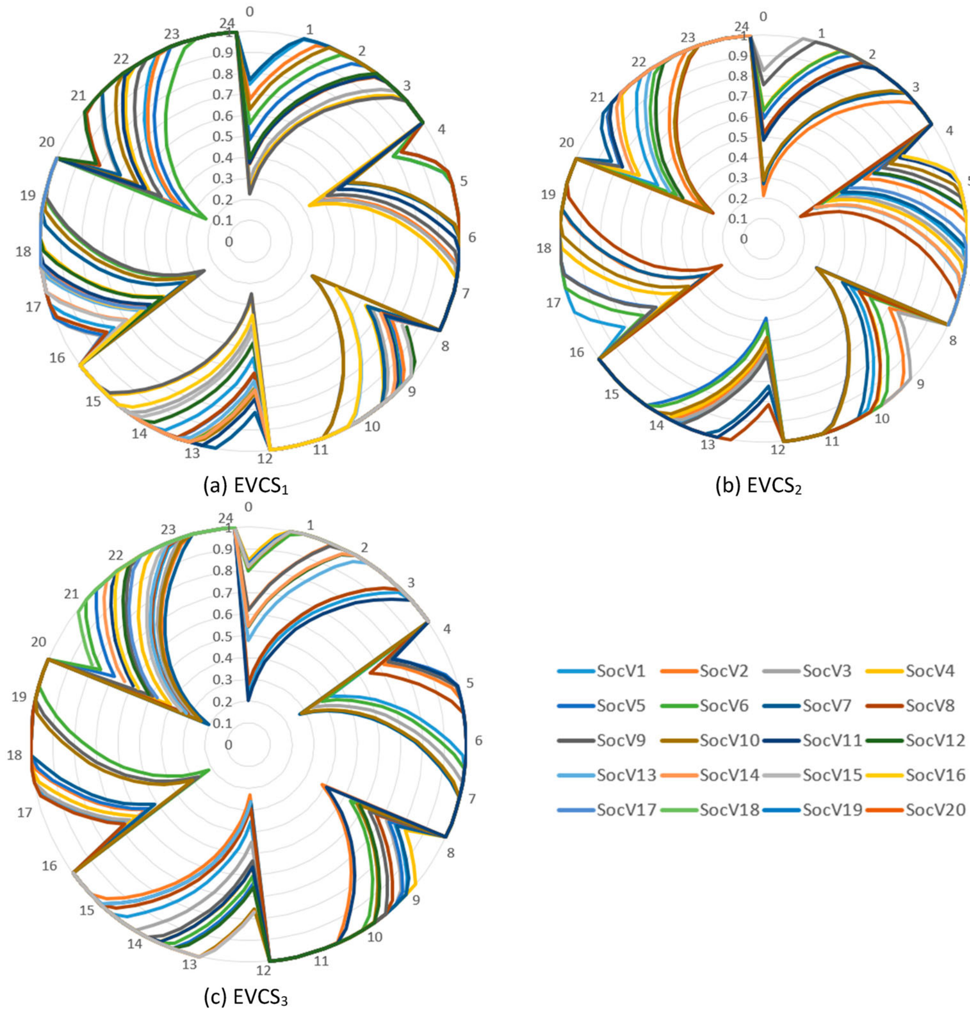

Figure 6. State of charge (SoC) of electric vehicles in the three electric vehicle charging stations (EVCSs) for case study I.

Table 2. Number of charging electric vehicles per station for case studies I and II.

	$EVCS_1$		$EVCS_2$		$EVCS_3$	
Period	Case I	Case II	Case I	Case II	Case I	Case II
$0.0 \leq t < 4.0$	12	20	11	21	16	19
$4.0 \leq t < 8.0$	11	18	17	15	12	27
$8.0 \leq t < 12.0$	16	17	10	16	13	30
$12.0 \leq t < 16.0$	16	19	11	19	16	15
$16.0 \leq t < 20.0$	17	24	10	19	11	15
$20.0 \leq t < 24.0$	12	20	14	21	19	26

Note: EVCS = electric vehicle charging station.

The charging/discharging power of the three BESS units is shown in Figure 8. A positive BESS power means charging status with increasing SoC (positive slope), while with negative power, the BESS discharges with decreasing SoC (negative slope). When the SoC remains at the upper limit of 0.85 or the lower limit of 0.2, the BESS is in the idle state, or no power exchange takes place. The performance parameters of the DN during the 24 h simulation were recorded and are shown in Figure 9.

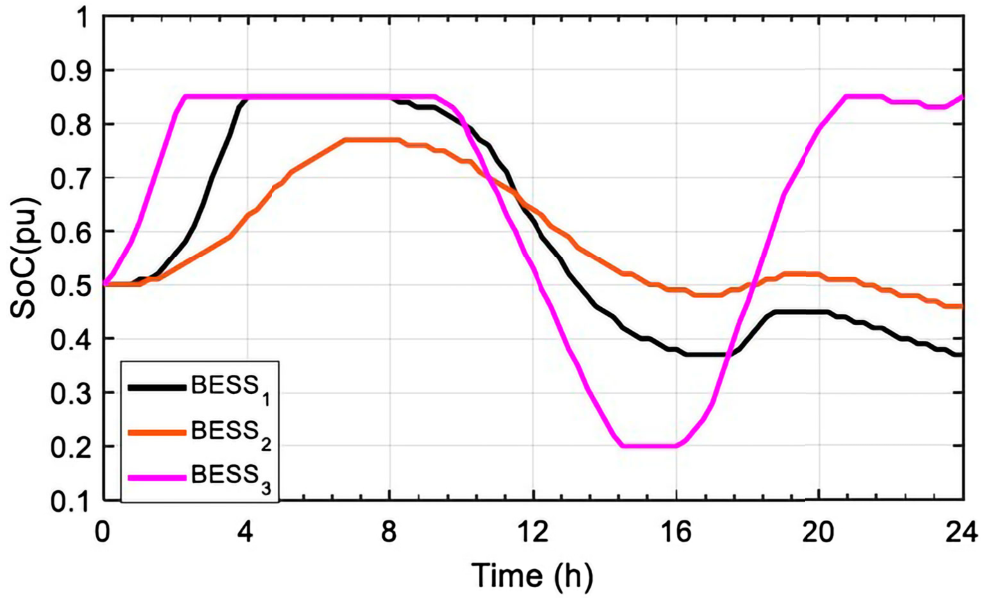

Figure 7. State of charge (SoC) of three battery energy storage system (BESS) units for case study I.

The parameters include the active and reactive losses, the TVD and SI, and the minimum/maximum voltage magnitude. The performance parameters vary with the operating conditions of the DN, and the minimum/maximum voltage values are within the voltage constraints.

4.2. Case study II

In this case study, the EVCS has 30 EV charging outlets available in every station for possible connections. The total number of possible chargers for the three stations is 90. As in the previous case, the EV works only in G2V mode, being a load added to the network demand, while the HBA optimizes the three WTGs with the BESS units to provide minimum daily energy losses. At every EVCS, a random number of EVs charges for 4 h according to their initial SoC. The random number of EVs per station lies between 15 and 30, and each charges at a constant power of 25 kW. The indicator parameters, including the active and reactive power losses, TVD and SI, are recorded during the simulation period of 24 h.

The total demand of the EVCS depends on the number of connected EVs during any period of operation. During the first period of the day ($0.0 \leq t < 4.0$), 20, 21 and 19 EVs are connected to $EVCS_1$, $EVCS_2$ and $EVCS_3$, respectively, as listed in Table 2. In other periods, different numbers of EVs are connected to the EVCSs. Consequently, the EVCS demand for every station randomly varies during the day, as shown in Figure 10. The EVCSs start with 500, 525 and 475 kW demand, and with time, these EVs stay connected until they reach an SoC of 100%. The EV charging duration depends on its initial SoC. Every 4 h, the EVs are changed, and new sets are connected to the three stations with different initial SoC values. This process repeats during the six periods of the day. The corresponding SoC statuses of all EVs in $EVCS_1$, $EVCS_2$ and $EVCS_3$ are shown in Figure 11. Radar charts are adopted to show the density distribution of EVs during the six periods of charging per day. The randomness of the EVs can be seen upon careful inspection of the figure. The EV density during the six periods varies, as not all charging outlets are connected to EVs.

As in case study I, the HBA optimizes the three BESS units to reduce network energy loss by reducing network loss at every stage of the simulation. The BESS units discharge to meet the extra demand

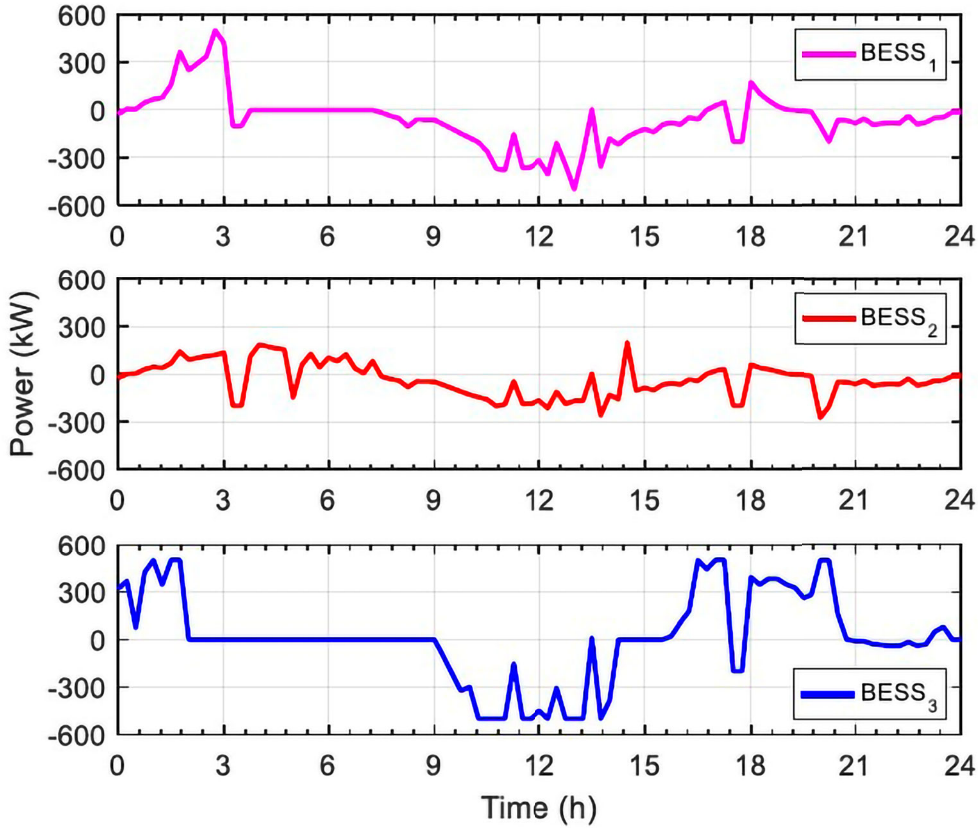

Figure 8. Power of three battery energy storage system (BESS) units for case study I.

when the demand of the network rises as a result of EV charging or a change in network demand. In this instance, the SoC of the BESS unit drops in line with the power drained, and conversely, the SoC rises when the BESS charges under low load conditions. The SoC of the BESS unit is anticipated to fluctuate as the network load varies along with the variation in EV load, as shown in Figure 12. Figure 13 shows the charging/discharging power of the three BESS units. Positive BESS power indicates a charging status with a rising SoC (positive slope), whereas negative power indicates a discharging status with a falling SoC (negative slope). The BESS is idle when there is no power exchange, *i.e.* when the SoC exceeds the upper limit of 0.85 or is less than the lower limit of 0.2.

The performance metrics of the DN throughout the 24 h simulation were noted and are displayed in Figure 14. The parameters include both active and reactive losses, the TVD and SI, and minimum/maximum voltage magnitudes. The minimum/maximum voltage values are within the voltage limits, and the performance parameters change depending on how the DN is running.

4.3. Comparison of network performance for case studies I and II

The calculated energy losses for the two case studies, along with the other performance parameters, are listed in Table 3. The daily energy loss for the second case study is higher than that for the first case, because of the excess number of EVs per EVCS. Consequently, more power is required from the utility; thus, the utility input energy is more significant for case study II. The energy losses, utility input energy, TVD and SI are decreased compared to the base case, as shown in Table 3. The active energy loss decreases by 63.5% and 61.1% for case studies I and II, while the corresponding reactive

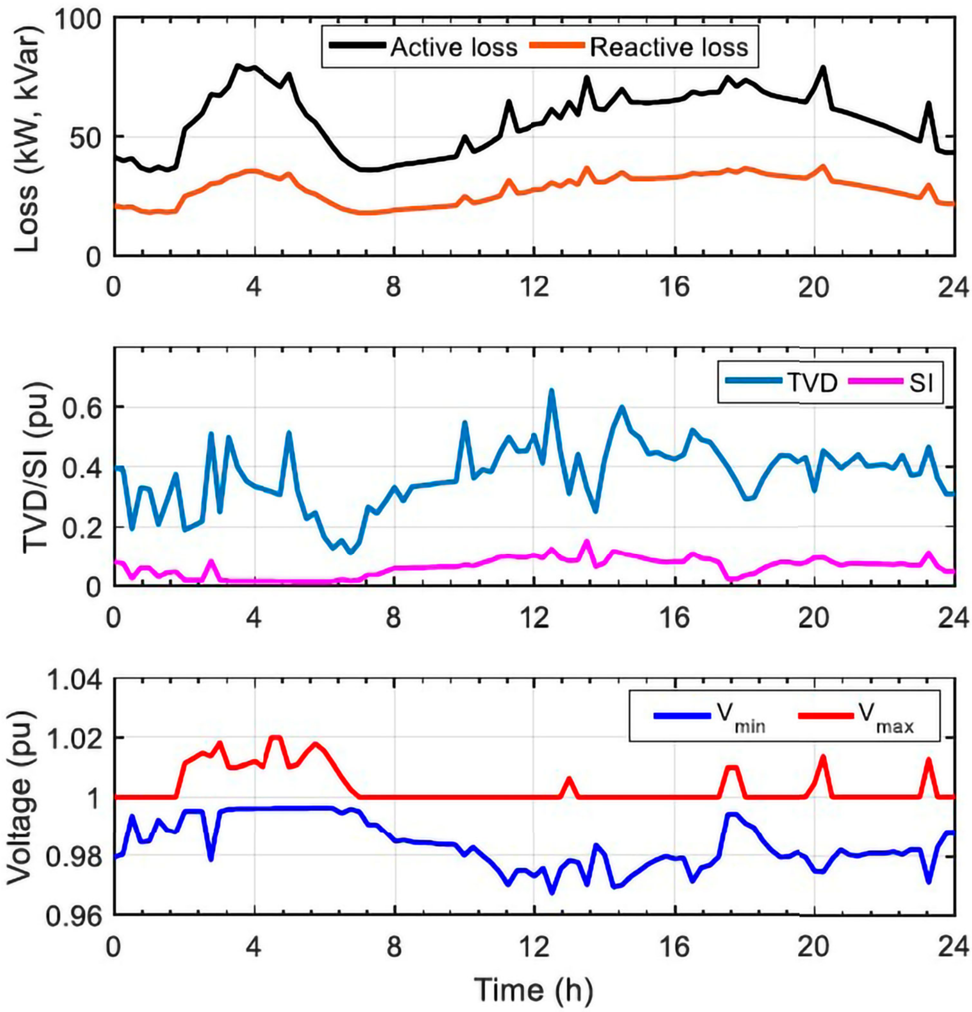

Figure 9. Performance parameters of the distribution system for case study I. TVD = total voltage deviation; SI = stability index.

energy loss decreases by 60.6% and 60.2%, respectively, as shown in Figure 15. The input energy of the utility decreases by 59.6% and 53.0% for case studies I and II. Moreover, both TVD and SI also decrease, by 75.4% and 75.8% and 76.3% and 76.8%, for case studies I and II, respectively. Furthermore, the minimum voltage improves from 0.9256 pu to 0.9839 and 0.9841 pu for case studies I and II, respectively.

Figure 16 shows the power exchanges from $BESS_3$, $EVCS_3$, P_{w3} and utility power (P_u) for case study I. When the BESS and EVCS are charging in the first 2 h, the utility needs to supply more power, especially with low wind power. In the period from 02:00 to 08:00 h, the BESS is in an idle state and the wind power has a prominent peak, so less utility power is needed. In the wind power valley, from 08:00 to 15:00 h, the utility supplies more power to support the load and EVCS, even with discharging of the BESS. In the last period, from 15:00 to 24:00 h, the wind power peaks, and hence the utility power is accordingly decreased while satisfying EVCS and BESS charging powers and network demand. Figure 17 shows the power exchanges from $BESS_3$, EVCS3, P_{w3} and P_u for case study II. Similar behaviour to that in case study I is recorded. The utility power responds to the changes in power of BESS, EVCS and wind power.

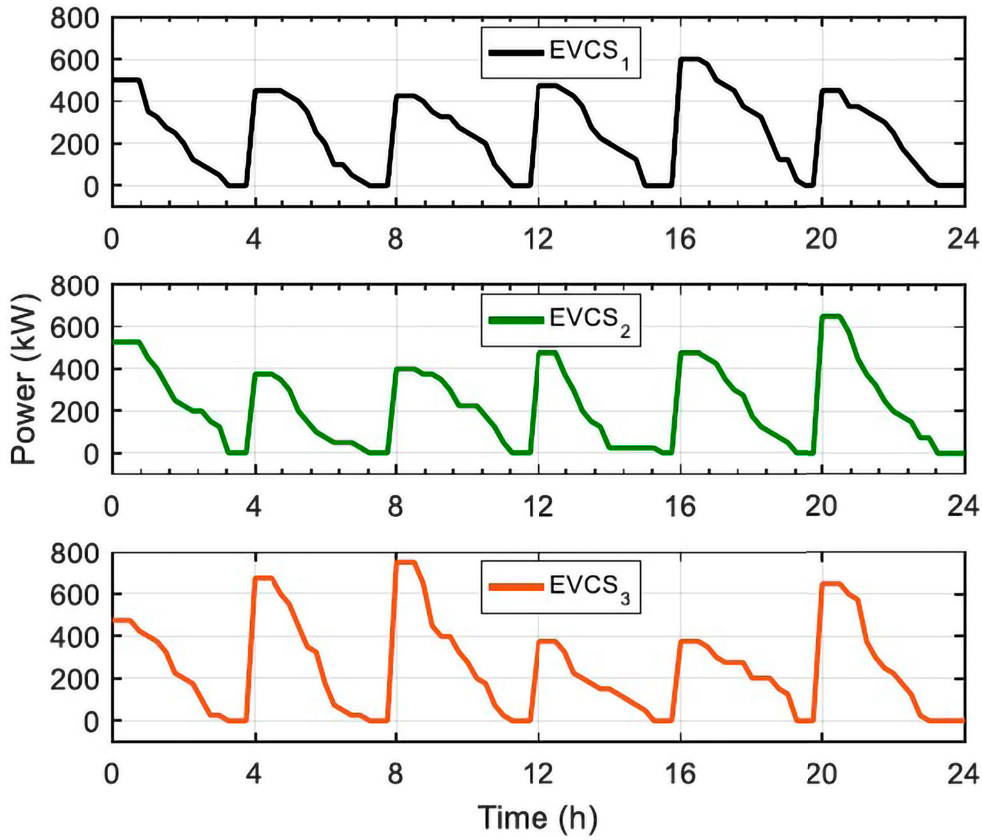

Figure 10. Total demand for the three electric vehicle charging stations (EVCSs) for case study II.

Table 3. Energy losses and utility energy of the distribution system for case studies I and II.

		Base case + EVCS/WT/BESS	
Parameter	Base case	Case study I	Case study II
Active energy loss (kWh/day)	3732.278	1363.97	1451.54
Reactive energy loss (kVar/day)	1697.127	668.92	675.41
Utility input energy (kWh/day)	79,802.70	32,234.35	37,527.96
Average TVD	1.5077	0.3714	0.3648
Average SI	0.2653	0.0628	0.0616
Average of V_{min}	0.9256	0.9839	0.9841
Average of V_{max}	1.0000	1.0032	1.0044

Note: EVCS = electric vehicle charging station; WT = wind turbine; BESS = battery energy storage system; TVD = total voltage deviation; SI = stability index.

4.4. Performance comparison of HBA with other algorithms

Using different metaheuristic optimization algorithms, the 69-bus DN is simulated and optimized to minimize the power loss under the same problem constraints and definitions. The optimization problem includes the optimal siting and sizing of three WT units. The HBA is compared to other algorithms, such as artificial ecosystem-based optimization (AEO) (Zhao, Wang, and Zhang 2020), marine predators algorithm (MPA) (Faramarzi *et al.* 2020) and PSO. All algorithms simulate the

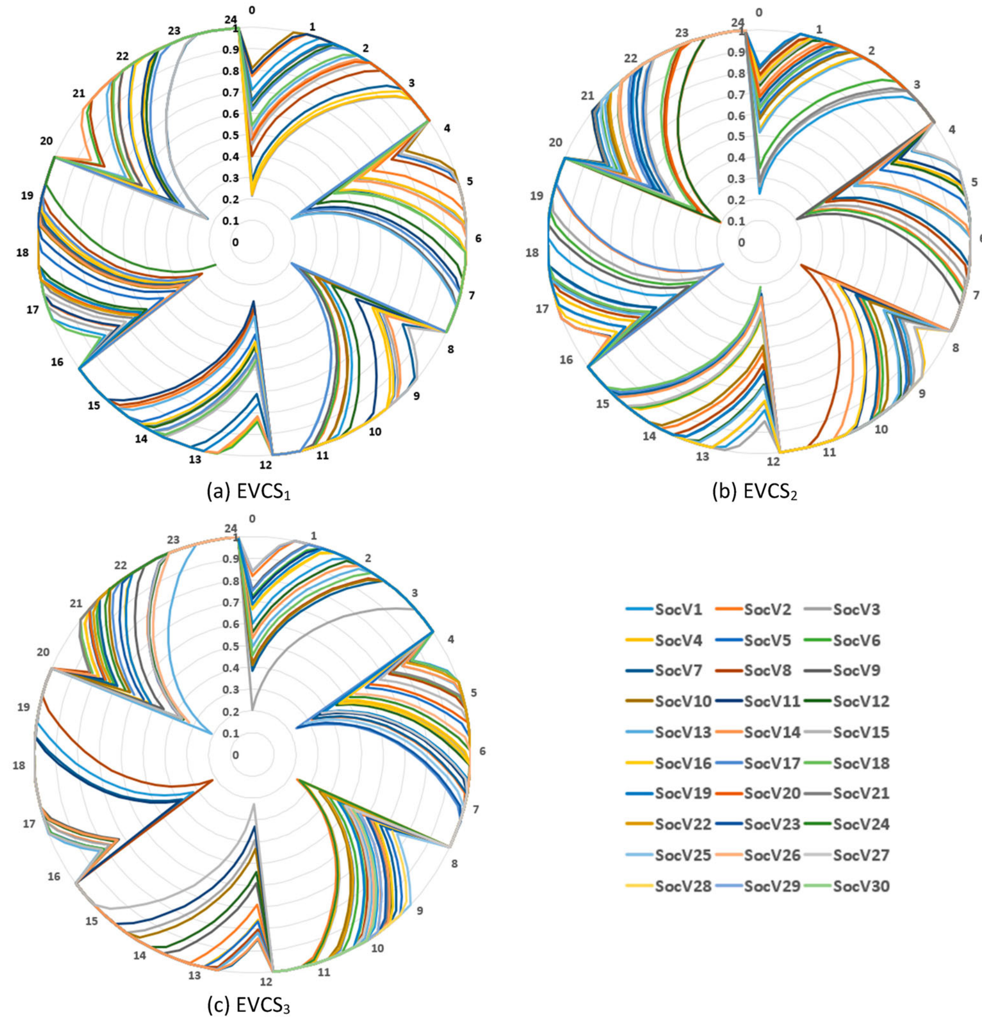

Figure 11. State of charge (SoC) of electric vehicles in the three electric vehicle charging stations (EVCSs) for case study II.

network, and the objective function is stored for further analysis. For comparison purposes, in all algorithms, the number of maximum iterations is fixed at 100, and the number of particles is also fixed at 100. The objective functions of all algorithms are plotted in Figure 18. Figure 18 demonstrates the superiority of the HBA compared to the other algorithms, in terms of speed and accuracy. The HBA reaches the steady-state value in a lower number of iterations compared to the other algorithms.

Owing to the stochastic behaviour of metaheuristic algorithms, the outputs of which can change from one run to another, the above problem is solved 30 times using each algorithm. The statistical results are listed in Table 4. The results show the HBA achieved the lowest minimum output and standard deviation. The box-plot visualization of the algorithms is shown in Figure 19. The HBA has lower outliers and better characteristics compared to the other algorithms.

A simulation case study is performed for contingency analysis, when the WT and BESS units are unavailable. In this case, the network has three EVCSs. The utility has to support the total demand of the network load and losses and the EV load during the 24 h of operation. The whole load of the three

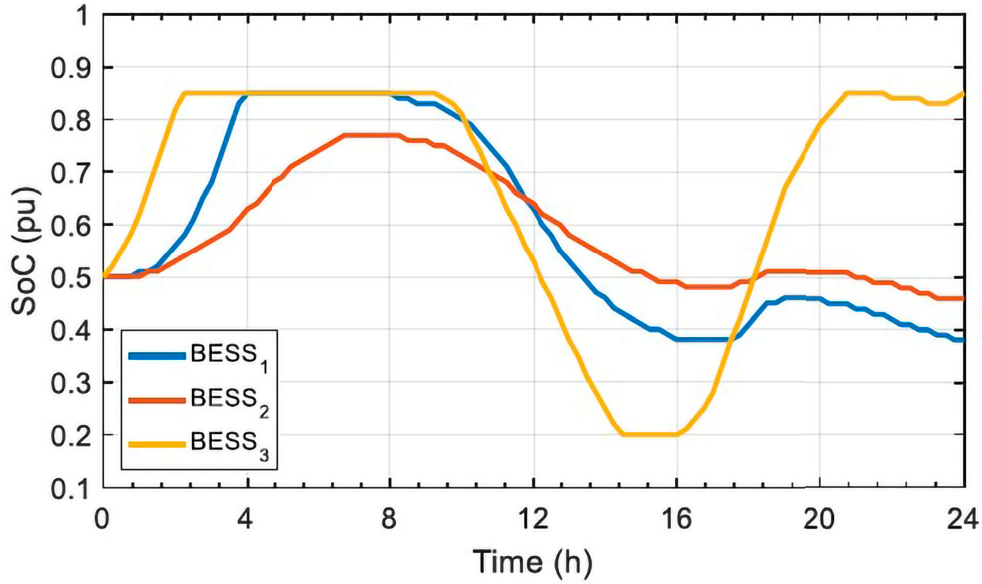

Figure 12. State of charge (SoC) of three battery energy storage system (BESS) units for case study II.

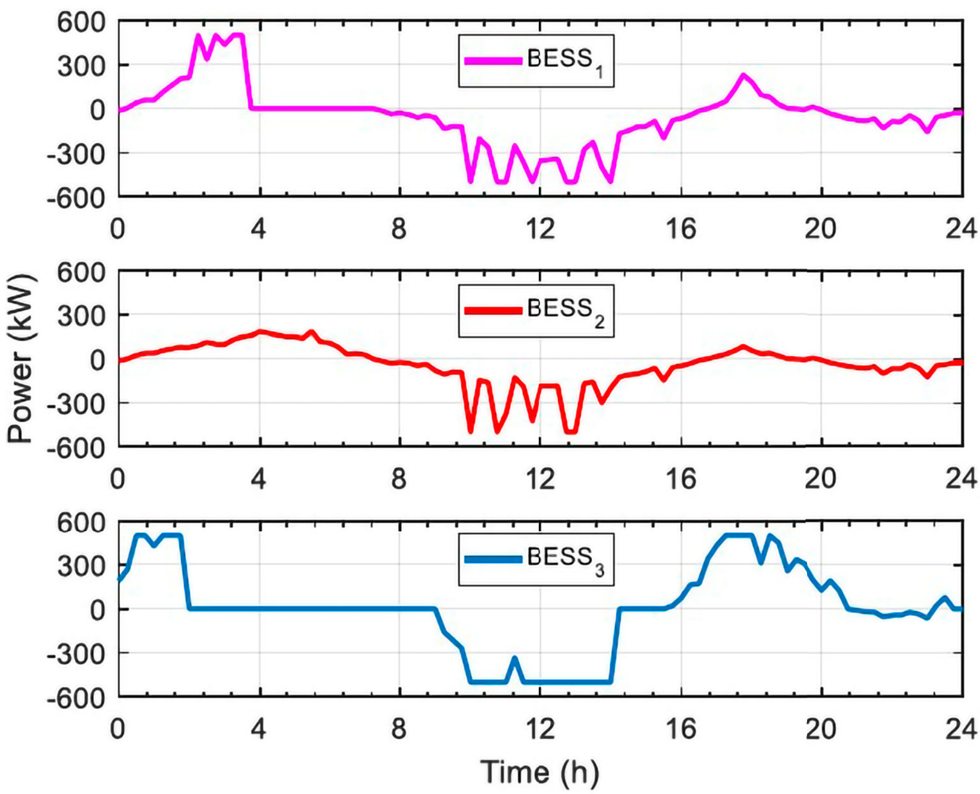

Figure 13. Power of three battery energy storage system (BESS) units for case study II.

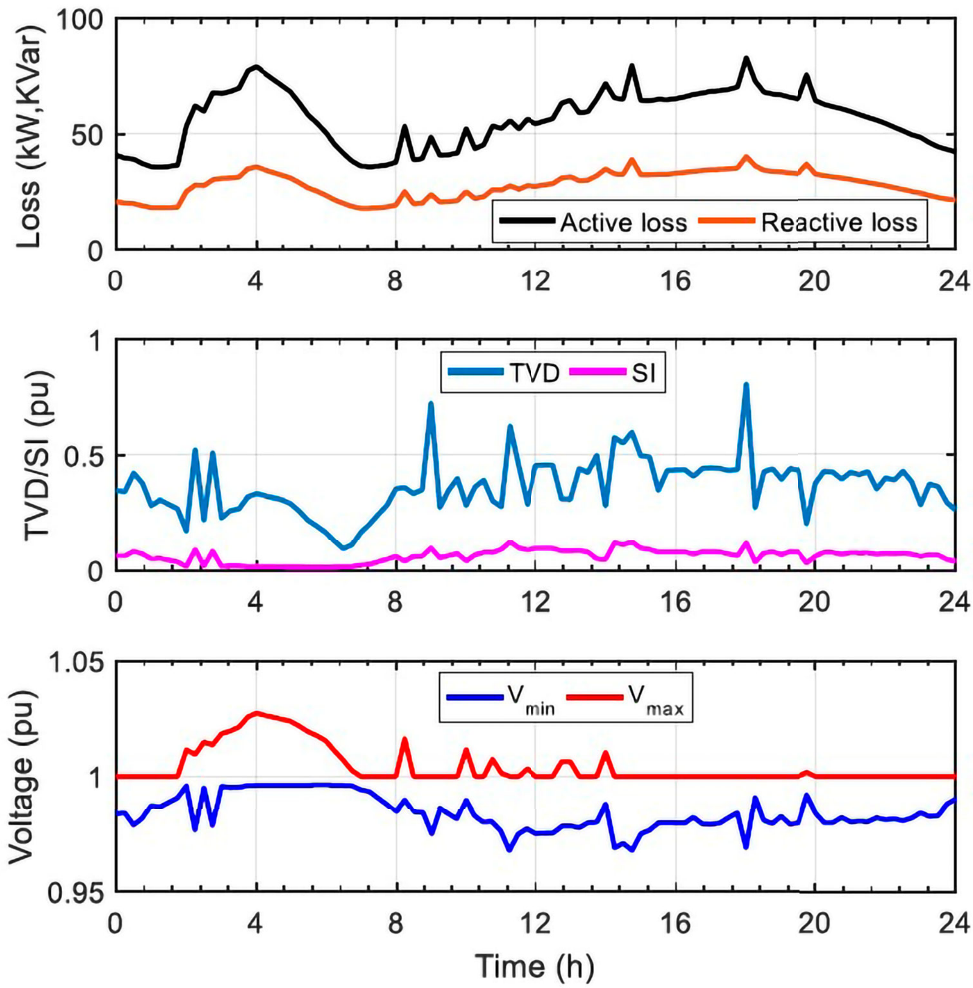

Figure 14. Performance parameters of the distribution system for case study II. TVD = total voltage deviation; SI = stability index.

Table 4. Performance comparison of the honey badger algorithm (HBA) with other algorithms.

Parameter	HBA	AEO	ASO	GTO	MPA	MRFO	PSO
Min	69.395	69.400	69.469	69.753	69.401	69.395	69.661
Max	69.595	71.025	72.712	74.023	70.136	71.395	74.440
Mean	69.413	69.665	70.342	70.940	69.562	69.633	70.266
Median	69.395	69.411	70.201	70.451	69.417	69.395	70.127
Std	0.0457	0.5010	0.7542	1.1391	0.2227	0.4890	0.9453
Var	0.0021	0.2510	0.5689	1.2975	0.0496	0.2391	0.8935

Note: AEO = artificial ecosystem-based optimization; ASO = Atom Search Optimization; GTO = Gorilla Troop Optimizer; MPA = marine predators algorithm; MRFO = Manta ray foraging optimization; PSO = particle swarm optimization.

EVCSs, network demand and utility power variations are shown in Figure 20. The utility supports the total demand instantaneously. The HBA applied a new constraint in this case study: the input feeder current cannot exceed the predefined value of 400 A. It is satisfying that the recorded maximum utility current is 292 A.

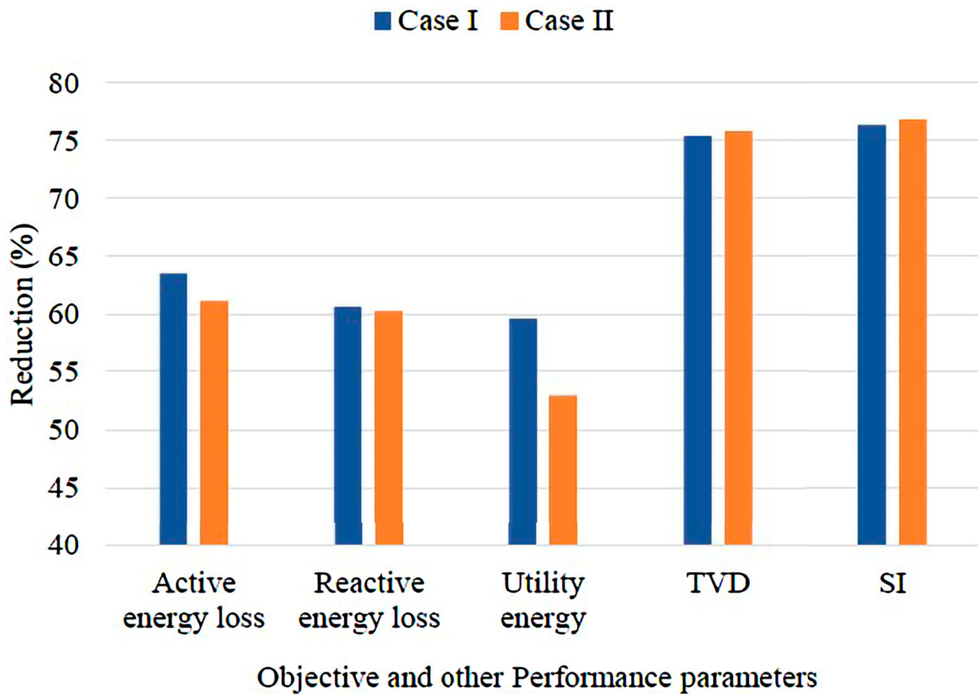

Figure 15. Reduction of performance parameters of case studies I and II compared with the base case. TVD = total voltage deviation; SI = stability index.

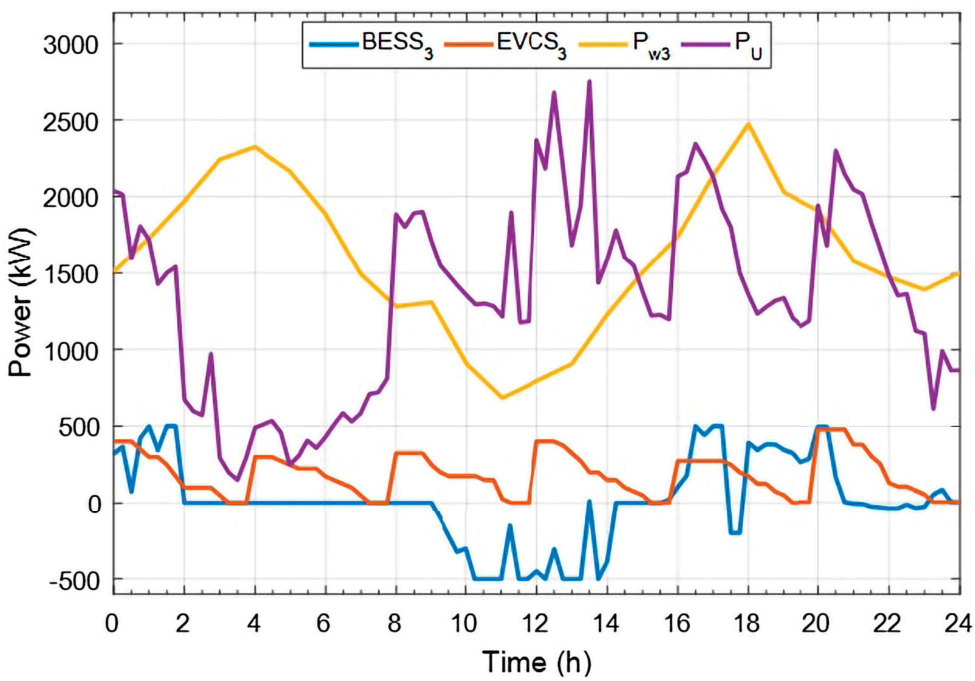

Figure 16. Battery energy storage system ($BESS_3$), electric vehicle charging station ($EVCS_3$), P_{w3} and utility power (P_u) power exchanges for case study I.

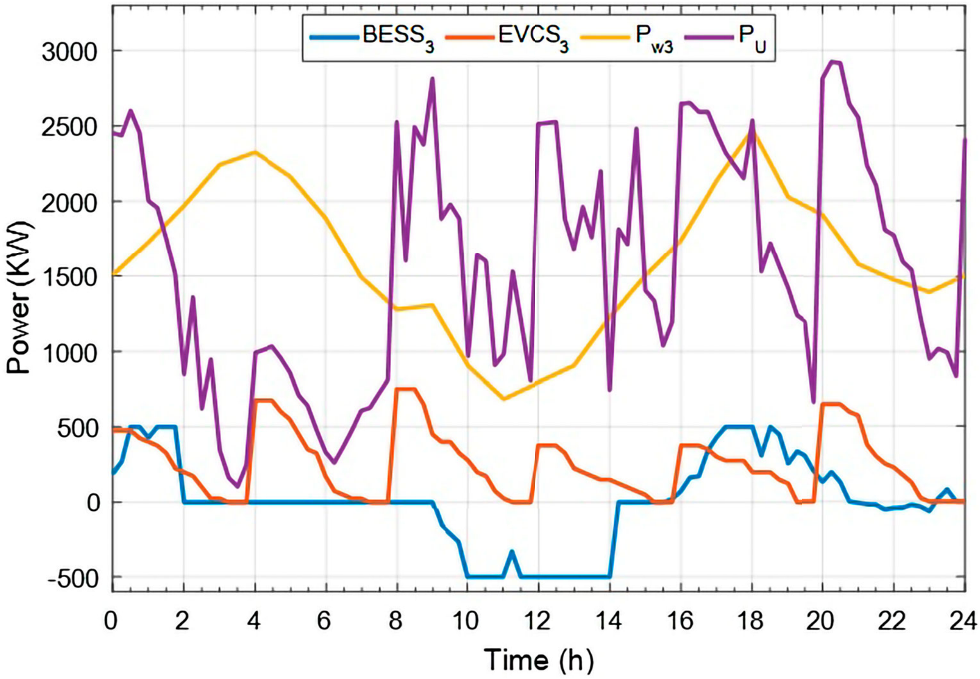

Figure 17. Battery energy storage system ($BESS_3$), electric vehicle charging station ($EVCS_3$), P_{w3} and utility power (P_u) power exchanges for case study II.

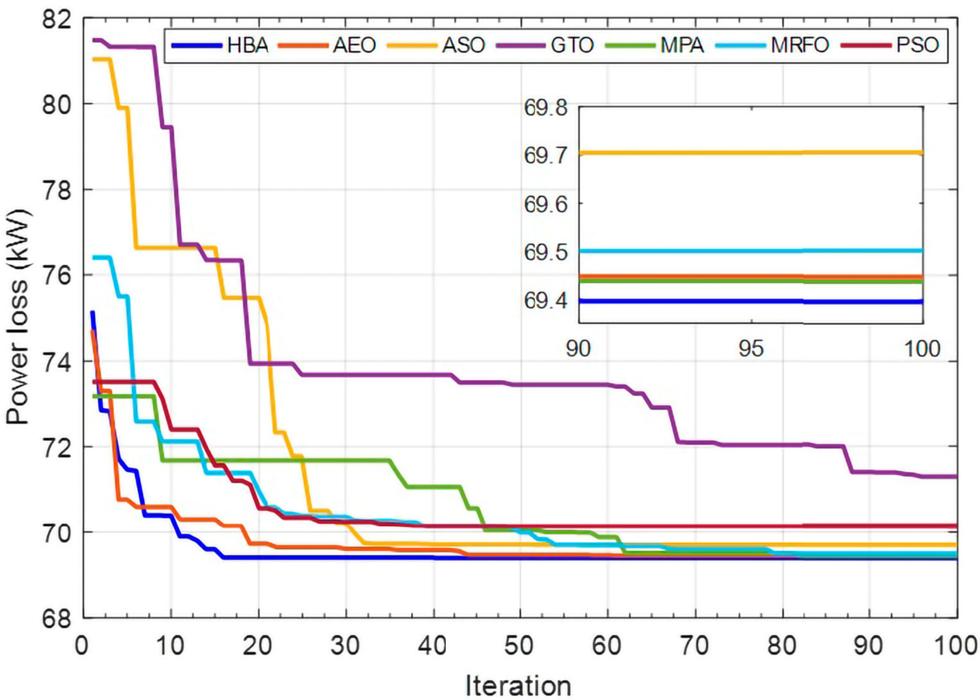

Figure 18. Speed and accuracy of the honey badger algorithm (HBA) compared to other algorithms.

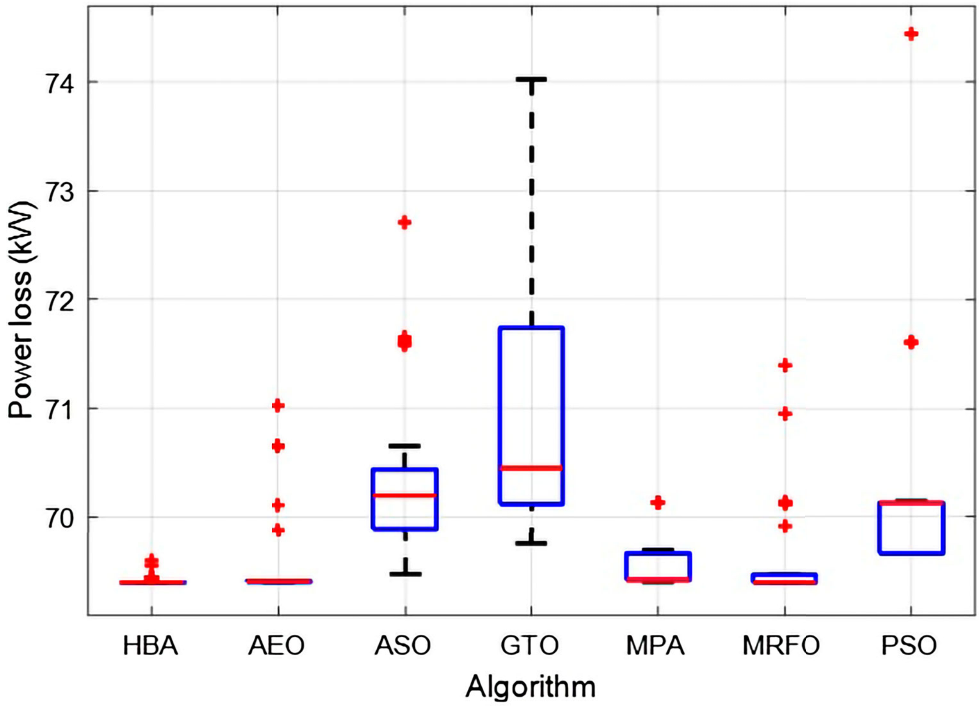

Figure 19. Performance of the honey badger algorithm (HBA) compared to other algorithms. AEO = artificial ecosystem-based optimization; ASO = Atom Search Optimization; GTO = Gorilla Troop Optimizer; MPA = marine predators algorithm; MRFO = Manta ray foraging optimization; PSO = particle swarm optimization.

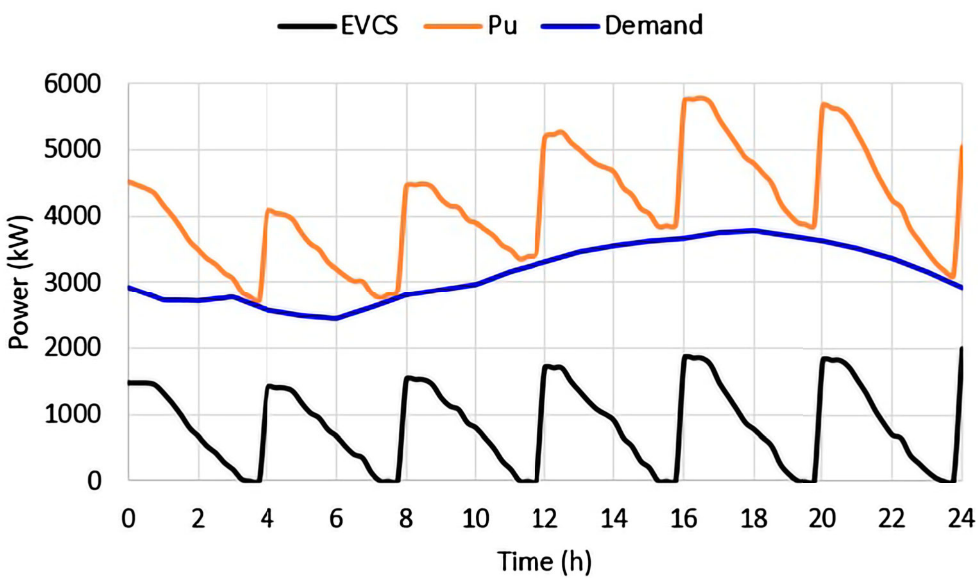

Figure 20. Variation of utility power (P_u) with demand and total load of electric vehicle charging stations (EVCSs) when wind and battery energy storage system powers are unavailable.

5. Conclusions

The characteristics of the EV demand modelling used in this study include the random distribution of EVs and the randomness of their SoC upon initial connection to the charging outlets. To take into account these two features of EV, a random number of EVs is assumed to visit each charging station, with a random SoC for each EV. The 69-bus DN, combined with WTGs and BESS units, is optimized by the cutting-edge metaheuristic HBA. The HBA provides an efficient and dependable solution to the issue being optimized. The best performance of the three WT-BESS units is taken into account when operating and controlling the three EVCSs. The proposed approach helps in achieving optimal operation of the DN with the three EVCSs during the hours of the day, while the WT and BESS units are effectively optimized. The active and reactive energy losses are decreased to 1364 kWh and 669 kVarh compared to the base case of 3732 kWh and 1697 kVarh, respectively, for case study I, and with slightly higher values for case study II. Moreover, the parameters of utility input energy, SI and TVD are also reduced, and the voltage profile is improved.

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data supporting the study are contained within the article.

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