Electrical Power and Energy Systems 168 (2025) 110675

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Optimal charging station placement of electric vehicles in the smart distribution network based on the mixed integer linear programming

Mehdi Veisi [a], Hossein Naderian [b], Mazaher Karimi [b,*]

[a] Department of Electrical Engineering, Sanandaj Branch, Islamic Azad University, Sanandaj, Iran
[b] School of Technology and Innovations, University of Vaasa, Wolffintie 34, 65200 Vaasa, Finland

ARTICLE INFO

Keywords:
Charging Station
Distribution Network
Electric Vehicles
Micro-turbine
Mixed Integer Linearized Programming

ABSTRACT

This article discusses the optimal placement of electric vehicle charging stations in the distribution network. The proposed approach is an optimization problem with the objective function equal to minimizing the cost of building charging stations and energy costs. Inevitably, minimizing the voltage deviation from the desired (reference) value is also considered in the objective function. The constraints of this problem include the equations of power flow, the restrictions governing electric vehicles and charging stations, and the limitations of network indicators. The mentioned problem can be described as mixed integer nonlinear programming (MINLP). Nevertheless, the MINLP optimization problem tends to run very slowly when the dimension of the grid increases significantly, and that's why it is unlikely that we obtain an absolute optimal solution. Consequently, a mixed integer linear programming (MILP) formulation that resembles the main problem is developed. Ultimately, a distribution network consisting of 69 buses is modeled in GAMS to evaluate the proposed formulation. In the proposed plan with the appropriate placement of electric vehicle charging stations, initially a favorable economic cost is obtained for the aforementioned stations. In the following, charging management at the aforementioned stations has caused the network operation status to improve. When EVs are absent, the maximum voltage drop is approximately 0.092p.u. and energy losses reach 2.08 MW. In contrast, with EVs present the voltage drop falls to about 0.037p.u. and energy losses drop to roughly 1.23 MW.

1. Introduction

Environmental issues and pollution intensification associated with fossil fuel consumption resulted in the expansion of utilizing novel technologies, particularly electric vehicles (EVs) [1]. EVs come in various types; for example, Plug-in Hybrid Electric Vehicles (PHEVs) connect to the power system to charge their batteries and meet their energy needs. EVs can be plugged into the grid in various places including homes, parking lots, and charging stations [2]. Charging EVs at homes or parking lots takes several hours but if they're plugged into charging stations, their charging time decreases to minutes [3]. Note that EVs connect to the power system between 15:00 and 24:00—peak hours when many vehicles are online. [4]. If energy management is not considered for EVs, EVs' power is supplied from the grid, which raises the power demand during the peak hours compared with base load (neglecting EVs). Consequently, voltage level drops and network losses increase, along with the possibility of overloading the distribution lines [5]. Moreover, the EV charging time in the charging station is low (e.g. 10 min). Hence, charging EVs at charging stations demands a significant amount of power because of the considerably low charging time. For example, if the EV's battery has a capacity of 20 kW, it requires approximately 120 kW from the upstream network to charge it within 10 min. Therefore, energy management is essential to improve network indicators in the presence of EVs. In managing EV energy, vehicles regulate their charging and discharging power to meet network operator goals (such as reducing energy loss and cost) as well as their own goal of lowering energy expenses [4,5]. More explicitly, charging stations should be located at distribution network points that won't harm the network indicators as well. So, we expect that the above-mentioned concerns will be resolved by the optimal placement of EV charging stations in the distribution network.

Researchers have done numerous works regarding the operation and planning of EVs. In papers [6,7], an EV charging power management is developed to diminish charging costs [6] as well as network losses [7]. According to their modeling, EVs only have control over their batteries' active charging power. Furthermore, based on minimizing the charging cost of EVs or network losses (which was their objective function) EVs

* Corresponding author.
E-mail address: mazaher.karimi@uwasa.fi (M. Karimi).

https://doi.org/10.1016/j.ijepes.2025.110675
Received 9 December 2024; Received in revised form 28 February 2025; Accepted 11 April 2025
Available online 15 April 2025

Nomenclature

Indices and Sets

i, j	Bus indices
k	Index of the linearization part of the circular equation
ref	Slack (reference) Bus
t	Time index
v	Electric vehicle index (EV)
φ_b	Bus set
φ_k	Set of the linearization part of the circular equation
φ_t	Time set
φ_v	Set of EVs

Parameters

AL	Matrix of coefficients (if there is a line between i and j buses, (i,j) entries of this matrix is equal to 1, otherwise it is zero)
b	Line Susceptance (p.u.)
CP	Cost of building a charging station ($)
CP_b	Base construction cost ($)
g	Line conductivity (p.u.)
P_b	Base power (p.u.)
PD	Active load (p.u.)
PE^{max}	Maximum charge rate (C-rate) of EVs (p.u.)
QD	Reactive load (p.u.)
SG^{max}	Upstream network capacity (p.u.)
SL^{max}	Line capacity (p.u.)
SP^{max}	Charging station capacity (p.u.)
V^{max}	Maximum value of the voltage magnitude (p.u.)
V^{min}	Minimum value of the voltage magnitude (p.u.)
V_{ref}	Voltage magnitude (p.u.) in slack bus
W^0	Primary energy stored in the EV battery at the moment of the EV is connected to the charging station (MWh)
η^{ev}	Efficiency of EVs
λ_b	Basic energy price ($/MWh)
λ^{cst}	Charging station energy price ($/MWh)
λ^{net}	Upstream network energy price ($/MWh)
$\Delta\alpha$	Angular deviation (radians)

Variables

PE	EV active power (p.u.)
PE^{ch}	EV charging power (p.u.)
PE^{dch}	EV discharge power (p.u.)
PG	Transmitted active power of the upstream network (p.u.)
PL	Active power passing through the line (p.u.)
PP	Active power of the charging station delivered to the network (p.u.)
PPG	Total active power of the charging station (produced by distributed generation) in p.u.
px	Binary variable to determine charging or discharging status of EVs
QG	Transmitted reactive power of the upstream network (p.u.)
QL	Line passing reactive power (p.u.)
V	Voltage magnitude (p.u.)
W	Energy stored in EV battery (MWh)
x	Binary variable of charging station construction
θ	Voltage angle or power angle (radiant)
ΔV	Voltage deviation (p.u.)

get their required energy during off-peak hours (1:00 to 8:00). Because the network safety margin for the voltage and the distribution lines overloading is appropriate during these hours, charging EVs during this interval doesn't affect the grid considerably. In this scenario, many EVs can be connected to the network. Nevertheless, they can't enhance the network indicators at critical moments such as peak load. For this purpose, references [8,9] considered both charging and discharging management of EVs. In their studies EVs inject power into the grid during peak hours and absorb power from the grid during off-peak hours. Active power injection into the grid reduces demand from the upstream network. Consequently, the voltage profile becomes smoother, and we observe a loss reduction as well. Also, references [10–12] demonstrate the presence of EVs along with distributed generations (DGs) in the power system. According to their discoveries, EVs can play the role of energy storage for DG. It is like solar cells that normally generate energy in daytime hours. Thus, EVs receive power from the network during these hours and deliver it back to the grid during peak hours. Hence network indicators improve, network reliability increases, and energy costs are significantly reduced. It is discussed in [13] that when PHEVs are plugged without having a program for coordinated charging, they start charging immediately. This uncoordinated power consumption can become problematic regarding the overload in transformers, causing casualties to increase. We should consider some economic objectives when charging these cars, including power loss reduction as well as preventing overload in transformers and feeders. Coordinated charging is designed based on reducing losses and increasing the load factor. In [14] to investigate the effect of charging PHEVs on the distribution network, four separate charging scenarios are considered. Charging is uncontrolled in the first and second scenarios, implying that PHEVs start charging as soon as they arrive at home without considering the charging limit. In the third and fourth scenarios, smart grids and load response discussion have been used to control the optimal charging of PHEVs. In [15], frequency control according to the network restrictions as well as dynamic changes during the day and PHEVs performance in vehicle-to-grid (V2G) mode were investigated. Also, it is declared that efficient frequency control demands a fast telecommunication infrastructure. An EV charge–discharge optimization (CDO) strategy that accommodates both grid-side and user-side demands is developed to mitigate the adverse effects of disordered EV charging on power distribution networks (PDN). To tackle the inaccurate estimation of the schedulable capacity issue of EVs in existing literature, a high temporal resolution dynamic spatiotemporal distribution simulation model for EVs is developed in [16]. Ref. [17] first discusses whether the manufacturer should introduce swapping-mode EVs (SEVs) and identifies the introduction conditions. It also investigates how two construction modes—manufacturer-construction mode and commission-construction mode—affect pricing decisions, EV demand, and profits. It then optimizes the government subsidy level to minimize total capital expenditure for a targeted EV adoption level. Reference [18] provides a novel approach to address uncertainties and enable demand response in EV charging station optimization. A two-stage optimization strategy is proposed in [18] that integrates robust optimization and explicit model predictive control (eMPC).

Recent studies have explored various strategies for optimizing the placement of EV charging infrastructure, focusing on improving efficiency and minimizing grid impact. In [19], a methodology is proposed that emphasizes demand-driven placement to reduce range anxiety and integrates user behavior into infrastructure planning. Apart from this research, the Trip Success Ratio (TSR) model is introduced to highlight the significance of driver convenience and diverse trip patterns to provide a user-centric perspective often overlooked in conventional methods [20]. Ref [21] advanced the field by incorporating multi-objective optimization and dynamic pricing models using a modified multi-objective particle swarm optimization (MOPSO). The proposed method was used to minimize power loss and voltage deviation coupled with dynamic price predictions using autoregressive integrated moving average (ARIMA) to enhance operator profitability and grid stability. A Bayesian network model to address qualitative and quantitative factors, emphasizing sustainability and technical feasibility is also analyzed in [22]. Lastly, [23] focused on integrating active and reactive power optimization for charging station placement, presenting an energy-balancing approach that minimizes losses in the distribution system. These studies collectively underscore the need for robust optimization frameworks that integrate user behavior, system constraints, and economic factors. This foundation supports our focus on optimal charging station placement with respect to cost and voltage stability.

In this paper, we propose a novel approach for the optimal location of EV charging stations in the distributed network. These stations are responsible for converting alternating current (AC) from the grid into direct current (DC) necessary for EV batteries. Therefore, the presence of an AC/DC converter in stations is compulsory. We predict that selecting an appropriate structure—such as a bidirectional converter capable of controlling power in both directions—will enable effective control of EV power. In this case, we expect that such stations can participate in distribution network power management. However, we should note that the number of charging stations in the distribution network is restricted. Thus, their optimal location should be determined in the first stage. Nevertheless, the planning of EV stations and the capability of EV stations power management on the distinct operation indices of the network are investigated at low works. Therefore, we discussed the optimal placement of EV charging stations in the distribution network. The objective function in this problem considers minimization of the cost of building charging stations and the cost of energy in addition to the minimization of the voltage deviation from the desired value. It is subject to AC power flow equations, EV and charging station models, and network operation restrictions. The previously mentioned problem has a mixed integer non-linear programming (MINLP) formulation. In the next section, mixed integer linear programming (MILP) equivalent to the main model of the problem is extracted. Because it is predicted that we can obtain the unique optimal solution in less computing time through this approach. Briefly, the innovations of this research are as follows:

- Problem formulation of placing EV charging stations in the distribution network to improve the grid's technical status.
- Harnessing vehicle to grid (V2G) capabilities in EVs and two-way power management including both active and reactive power for charging stations.
- Optimal sitting of the EVs charging station according to network operator objectives, i.e. minimizing of energy cost and voltage deviation, and station planner objective, i.e. minimizing of building cost of charging station.

In the second part of the paper, the basic formulation of charging station placement is described. In the third part, the associated linear approximation model is extracted. Numerical results are analyzed in the fourth section. Eventually, the conclusions are discussed in the last section.

2. Proposed problem model

The optimal placement of EV charging stations in the distribution network is an optimization problem consisting of an objective function as well as several constraints. The objective function of the proposed problem aims to minimize the total cost of construction and energy plus voltage deviation from the reference value, which is expressed in normalized form. Moreover, the problem is constrained by power distribution equations, network indicator limits (such as line power and bus voltage), and the mathematical equations governing EV charging stations. Generally, the mathematical model of the proposed problem is as follows:

$$\min \quad \frac{1}{CP_b}\sum_{i\in\varphi_b} x_i CP_i + \sum_{t\in\varphi_t}\frac{1}{\lambda_b P_b}\left(\lambda_t^{net} PG_{ref,t} + \lambda_t^{cst} PPG_{i,t}\right) + \sum_{i\in\varphi_b}\sum_{t\in\varphi_t}\left(\frac{V_{i,t}-V_{ref}}{V_{ref}}\right)^2 \tag{1}$$

s.t.

$$PG_{i,t} + PP_{i,t} - PD_{i,t} = \sum_{j\in\varphi_b} AL_{i,j} PL_{i,j,t} \forall \mathrm{i,t} \tag{2}$$

$$QG_{i,t} - QD_{i,t} = \sum_{j\in\varphi_b} AL_{i,j} QL_{i,j,t} \forall \mathrm{i,t} \tag{3}$$

$$PL_{i,j,t} = g_{i,j}(V_{i,t})^2 - V_{i,t}V_{j,t}\left\{g_{i,j}\cos(\theta_{i,t}-\theta_{j,t}) - b_{i,j}\sin(\theta_{i,t}-\theta_{j,t})\right\}\forall \mathrm{i,j,t} \tag{4}$$

$$QL_{i,j,t} = -b_{i,j}(V_{i,t})^2 + V_{i,t}V_{j,t}\left\{b_{i,j}\cos(\theta_{i,t}-\theta_{j,t}) + g_{i,j}\sin(\theta_{i,t}-\theta_{j,t})\right\}\forall \mathrm{i,j,t} \tag{5}$$

$$\theta_{i,t} = 0 \forall \mathrm{i} = \mathrm{ref}, \mathrm{t} \tag{6}$$

$$V_i^{\min} \le V_{i,t} \le V_i^{\max} \forall \mathrm{i,t} \tag{7}$$

$$(PL_{i,j,t})^2 + (QL_{i,j,t})^2 \le \left(SL_{i,j,t}^{\max}\right)^2 \forall \mathrm{i,j,t} \tag{8}$$

$$(PG_{i,t})^2 + (QG_{i,t})^2 \le (SG_i^{\max})^2 \forall \mathrm{i,t} \tag{9}$$

$$PP_{i,t} = PPG_{i,t} - \sum_{v\in\varphi_v} PE_{v,t} \forall \mathrm{i,t} \tag{10}$$

$$-SP_i^{\max} x_i \le PPG_{i,t} \le SP_i^{\max} x_i \forall \mathrm{i,t} \tag{11}$$

$$\mathrm{W}_{v,t} = \mathrm{W}_{v,t}^0 + \eta_v^{ev} PE_{v,t}^{ch} - \frac{1}{\eta_v^{ev}} PE_{v,t}^{dch} \forall \mathrm{v,t} \tag{12}$$

$$PE_{v,t} = PE_{v,t}^{ch} - PE_{v,t}^{dch} \forall \mathrm{v,t} \tag{13}$$

$$0 \le PE_{v,t}^{ch} \le PE_v^{\max}(1 - px_{v,t}) \forall \mathrm{v,t} \tag{14}$$

$$0 \le PE_{v,t}^{dch} \le PE_v^{\max} px_{v,t} \forall \mathrm{v,t} \tag{15}$$

$$0 \le W_{v,t} \forall \mathrm{v,t} \tag{16}$$

Equation (1) expresses the objective function of the proposed problem. It includes the sum of the construction and energy costs plus the voltage deviation from the desired value, where all terms of the objective function are expressed as a percentage [24]. Consequently, there is no need to present a multi-objective problem. In equation (1), each function is normalized so that all three have equal importance. The normalized value of each function is equal to the value of the function divided by a base value of the function. In this situation, the relative value of each function in equation (1) is calculated, which are unit-less. In this situation, the sum of the three mentioned functions was considered as the objective function in equation (1). Note that the planning cost $\sum_{i\in\varphi_b} x_i CP_i$, operation cost $\sum_{t\in\varphi_t}\left(\lambda_t^{net} PG_{ref,t} + \lambda_t^{cst} PPG_{i,t}\right)$, and voltage profile function $\sum_{i\in\varphi_b}\sum_{t\in\varphi_t}\left(V_{i,t} - V_{ref}\right)^2$, are in \$, \$, and p.u. (per unit), respectively. To ensure that the various functions in equation (1) share consistent units, their relative values were incorporated into equation (1). Constraints (2)–(6) address the power distribution equations. Specifically, equations (2) and (3) [25–28] define the active and reactive power balance at each bus for every hour, while equations (4) and (5) describe the active and reactive power flow through each line. Equation (6) specifies the voltage (or power) angle at the reference (slack) bus across all hours. It should be noted that only the charging stations in the grid are considered in this problem, so PG and QG represent the active and reactive powers of the upstream network that are given to the medium pressure distribution network, respectively [29–32]. We assumed that the mentioned distribution network is connected to the upstream network through the reference bus. Hence, PG and QG have values only in the reference bus and are equal to zero in other buses [33]. Constraints (7)–(9) restrict network indicators as follows: (7) limits bus voltage magnitude, (8) restricts line throughput, and (9) sets the upstream network power limit for every simulation hour [33].

The mathematical equations governing the EV charging stations are illustrated in constraints (10–16). More explicitly, equation (10) shows that both the power delivered to EVs and any excess charging capacity are supplied to network loads, as defined in equation (2). But according to the equation (10), EVs must perform their charging and discharging operations at the charging station [34–37]. Furthermore, the restriction of EV charging station capacity is represented in equation (11). According to this formulation if the binary variable x is equal to q, then the charging station should be built into the corresponding bus. On the other hand, if the binary variable x is equal to zero, the charging station will not be built on the corresponding bus. The reason is that it can't be economically justified. Equations (12–16) express the behavior of EVs as well. Equation (12) expresses the energy stored in the EV batteries. Equation (13) shows that the EVs' power is equal to the charge and discharge powers. Indeed, it is worth mentioning that according to the equations (14) and (15), the charging and discharging power at the same time do not have a value [38–41]. In other words, if the charging power had a value other than zero, then the discharging power must be equal to zero and vice versa [42–44]. Finally, the equation (16) refers to the positive amount of energy stored in EV batteries [45].

In the proposed scheme, the location of electric vehicle charging stations is considered, which is generally a long-term problem. The proposed scheme also includes the energy management problem in the distribution network, which is a 24-hour short-term problem. In the problem of locating the charging station, it is necessary to determine the location of this station in the network. Its active and reactive power management is part of the energy management problem. Determining the location of the station is independent of time. Therefore, it can be combined with the 24-hour energy management problem without the need for a long-term problem model. These conditions hold in problems (1)-(16).

3. Linear modeling of the proposed scheme

Constraints (4–5) and (8–9) as well as the third term of the objective function are nonlinear mathematical equations. In addition to this, equations (4–5) are also non-convex. The problem has binary variables, so the model associated with the proposed problem (1–16) is non-convex MINLP. Because of its non-convexity, different solvers obtain distinctive solutions. They are solved by numerical methods based on repetition as well [46–50]. Therefore, their computing time is high [24,33,45]. To tackle this problem, our paper uses a mixed linear approximation model equivalent to the proposed original one. The linearization process is as follows [51]:

A) *Linear estimation of power flow constraints:* The nonlinear constraints of this section include equations (4–5). To linearize these equations, we considered two basic hypotheses:

- The voltage angle between the distribution line terminals is less than 6 degrees, which is equivalent to 0.105 rad.
- Since the voltage magnitude of buses in the distribution network should be between 0.95 and 1.05p.u., the voltage magnitude of buses is close to one p.u.

It should be noted that according to [24,33,45], in the distribution network, the voltage angle deviation between the two buses at the beginning and end of the distribution line is generally less than 6 degrees. Therefore, the first hypothesis is true in the distribution network. Also, it is expected that the voltage magnitude is between 0.95 and 1.05p.u. in the power system and distribution network. In other words, it is expected that the maximum voltage drop and the maximum overvoltage will not exceed 0.05p.u. Therefore, the magnitude of the voltage deviation is much less than the voltage magnitude or 1p.u. Based on this, the second assumption is also true in the power system and distribution network. According to the mentioned hypothesis, the bus voltage can be expressed as $1 \pm \Delta V$, where the absolute value of the expression ΔV is significantly less than 1. According to the first hypothesis $\cos(\theta_{i,t} - \theta_{i,t})$ and $\sin(\theta_{i,t} - \theta_{i,t})$ it will be equal to 1 and $(\theta_{i,t} - \theta_{i,t})$ respectively. The values of ΔV^2, $\Delta V \times (\theta_{i,t} - \theta_{i,t})$ and $\Delta V_i \times \Delta V_j$ are so small that these terms are omitted in this research. Therefore, we can rewrite equations (4–5) as follows [51]:

$$PL_{i,j,t} = \left\{ g_{i,j}(\Delta V_{i,t} - \Delta V_{j,t}) + b_{i,j}(\theta_{i,t} - \theta_{j,t}) \right\} \quad \forall i,j,t \tag{17}$$

$$QL_{i,j,t} = -\left\{ g_{i,j}(\theta_{i,t} - \theta_{j,t}) + b_{i,j}(\Delta V_{i,t} - \Delta V_{j,t}) \right\} \quad \forall i,j,t \tag{18}$$

B) *Linear approximation of circular equations*: Equations (8)–(9) are non-linear relationships. In other words, they represent the circle's inequality, which is the magnitude of active and reactive power changes inside the circle with the radius equal to the maximum value of nominal power. Fig. 1 depicts the determination of linear equations corresponding to the circular plane expressed in equation (19). Therefore, we obtained a circular page by sharing several square pages. For instance, the linear expression of the circular page is in the form of equation (20) according to Fig. 1.

$$y^2 + x^2 \le r^2 \tag{19}$$

$$y \le r,\ y \ge -r,\ x \le r \,\&\, x \ge -r \tag{20}$$

Based on Fig. 1, equation (20) suffers from a large linearization error. To reduce it, we should increase the number of square plates with a different angle from the horizontal axis. Therefore, the circumference of the circle (which is 360 degrees) is divided into equal parts $\Delta\alpha$ in the first step. Then the equation of the line is calculated for each $k.\Delta\alpha$, where k represents the linearization part indices. Ultimately, the equation associated with the calculated line is adjusted to be less than the circle's radius (r). In this case, the linear approximation equation of the circular plane is expressed as the following relationship:

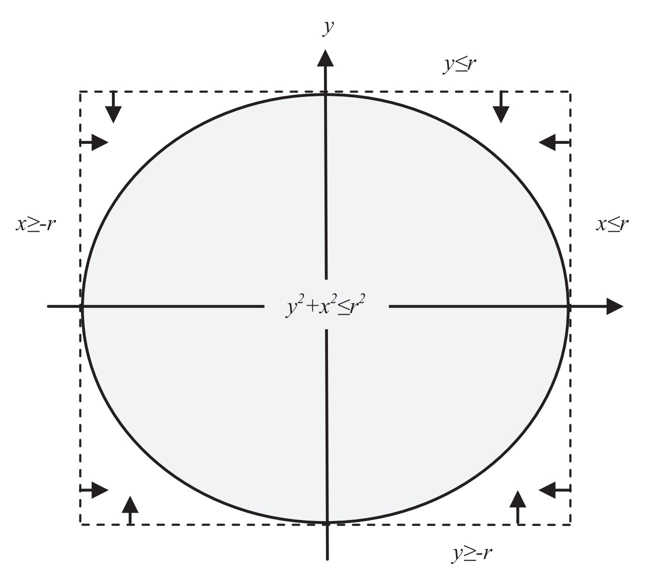

Fig. 1. Linear expression of a Circular Plane [24].

$$x\cos(k\Delta\alpha) + y\sin(k\Delta\alpha) \le r \quad k \in \varphi_k = \{0, 1, \ldots, n_k - 1\} \tag{21}$$

In the above equation, n_k is equal to the number of linearization parts. For instance, if 180 square plates are used to linearize a circular plate then n_k is equal to 180, and $\Delta\alpha$ will be equal to 2 degrees. In this case, the planes $x \le r$ and $y \le r$, corresponding to $k = 0$ and $k = 45$, respectively. Therefore, the linear approximation of equations (8–9) is as follows according to the explanations:

$$\cos(k \times \Delta\alpha) \times PL_{i,j,t} + \sin(k \times \Delta\alpha) \times QL_{i,j,t} \le SL_{i,j}^{\max} \quad \forall i, j, t, k \tag{22}$$

$$\cos(k \times \Delta\alpha) \times PG_{i,t} + \sin(k \times \Delta\alpha) \times QG_{i,t} \le SG_{i}^{\max} \quad \forall i, t, k \tag{23}$$

C) *Linear equation of voltage deviation from the desired value* (*the objective function's third term*): Based on the hypothesis considered for the voltage magnitude, the third term of the objective function is expressed as follows:

$$\sum_{i\in\varphi_b}\sum_{t\in\varphi_t}\left(\frac{\Delta V_{i,t}}{V_{ref}}\right)^2 \tag{24}$$

Thus to linearize (24), the following equation is used first:

$$\sum_{i\in\varphi_b}\sum_{t\in\varphi_t}\left|\frac{\Delta V_{i,t}}{V_{ref}}\right| \tag{25}$$

Note that $\Delta V_{i,t}$ is generally negative because most loads receive power from the upstream network and voltage drops in the distribution lines keep all bus voltages below the reference level.

$$-\sum_{i\in\varphi_b}\sum_{t\in\varphi_t}\frac{\Delta V_{i,t}}{V_{ref}} \tag{26}$$

Hence, the final model of the proposed problem is:

$$\min \quad \frac{1}{CP_b}\sum_{i\in\varphi_b} x_i CP_i + \sum_{t\in\varphi_t}\frac{1}{\lambda_b P_b}\left(\lambda_t^{net} PG_{ref,t} + \lambda_t^{cst} PPG_{i,t}\right) - \sum_{i\in\varphi_b}\sum_{t\in\varphi_t}\frac{\Delta V_{i,t}}{V_{ref}} \tag{27}$$

s.t.:

Constraints (2), (3), (6), (7), (10)-(18), (22), (23) (28)

$$V_{i,t} = 1 + \Delta V_{i,t} \quad \forall i, t \tag{29}$$

4. Numerical results

4.1. Problem's configuration

We implemented the linearized mathematical problem on the 69-bus radial distribution network, which is represented in Fig. 2. Also, characteristics of the distribution lines and substations as well as their corresponding peak load data are discussed in [52]. Slack bus is 1, and its voltage is 1 ∠0. Lower and upper value of voltage is 0.95 and 1.05p.u. [53–56]. We obtained the value of active and reactive bus load in other hours by multiplying the active and reactive load of the peak hour and the load coefficient curve [57–59]. This load factor curve is shown in Fig. 3 [51], and the electrical energy price received from the upstream network is illustrated in Fig. 4 [51]. We should note that the selling price of microturbine power is lower than the upstream grid energy price, and its price is always fixed at $15/MW. In other words, we assumed that EVs receive energy from microturbines at a fixed price.

In what follows, we considered some assumptions in our simulations before discussing the results:

- The minimum and maximum voltage magnitudes are equal to 0.9 and 1.05p.u., respectively.
- The base power and voltage of the proposed grid are equal to one megavolt ampere (1 MVA) and 12.66 kV.
- Charging stations with the supplying power of microturbines can be built in all buses.
- Microturbines are connected to the grid and can supply any excess power beyond what is drawn by EVs.

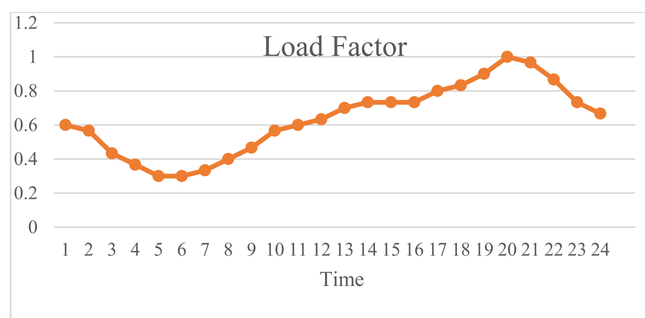

Fig. 3. Load Factor Curve [5].

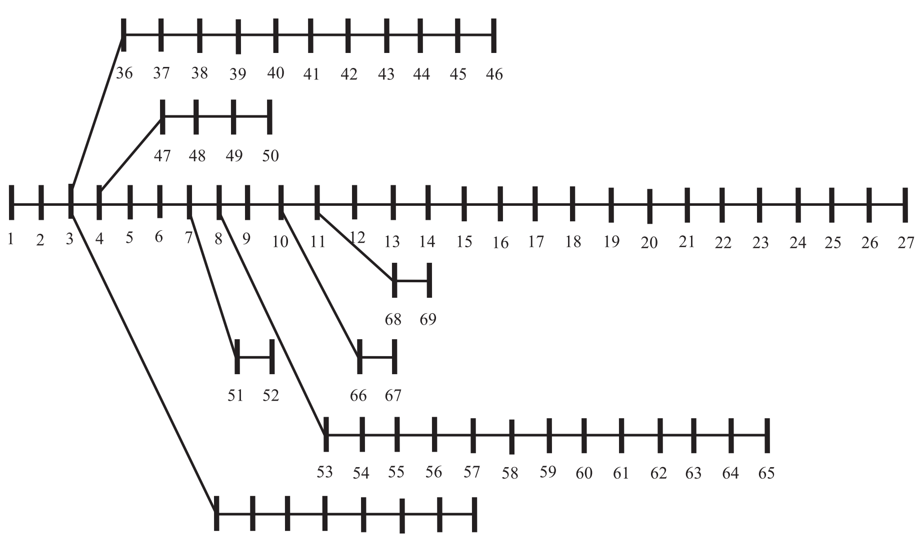

Fig. 2. Radial Distribution Network Structure of the 69 Bus Grid [52].

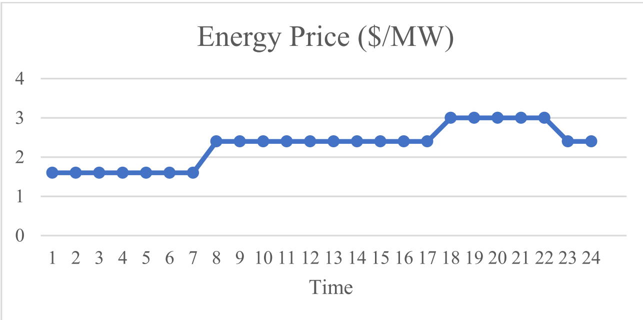

Fig. 4. Daily Prices of Electric Energy [51].

- The capacity of microturbines is considered equal to 0.5 MVA.
- The EVs specifications such as battery capacity, charging rate, etc. are discussed in references [5,24] and there are a maximum number of 500 EVs in the grid.
- EVs visit the charging station once during the 24 h, where they can be charged or discharged. In other words, EVs leave the house between 6:00 and 8:00 to work, and they return home at 16:00.
- Between 6:00 and 8:00, 30 % of EVs return to the charging stations, maintaining a constant number during that period.
- Approximately 10 % of EVs visit the stations at 16:00, 30 % at 17:00, 15 % at 18:00, and 7.5 % each at 19:00 and 20:00.

4.2. Results

We coded the proposed framework in GAMS software and solved it by CPLEX solver [60]. The inputs to the problem are the parameters that were introduced in the Symbol List section and their values are presented in Section 4.1. The output of the problem are the variables that were introduced in the Symbol List section, and their values are determined by the GAMS software. Their values are presented in Section 4.2. In GAMS, the data for the parameters and indices from the Symbol List are defined according to Section 4.1. Next, the variables for the proposed problem are introduced and the formulation of problem (27)-(29) is implemented. The optimal solution is then obtained using the integrated CPLEX solver, which eliminates the need to code a custom solution algorithm. Finally, executing the program produces an output listing the number of variables in problem (27)-(29), with selected values presented below.

A) *Comparison of MINLP and MILP models*: In this section, the results of two MINLP and MILP models for the proposed design are presented. According to Table 1, the number of places for the charging station is the same as both problems and there are no calculation errors in terms of the location of the charging station. In addition to this, the difference in amplitude and voltage angle for the two models of the mentioned problem is around 0.5 % and 0.4 %, respectively. The difference of the total active and reactive power produced from the point of view of the upstream network for both models of the mentioned problem is around 2.9 % and 2.5 %, respectively as well. But it should be noted that the calculation time for the MINLP model is 4751 s, but the calculation time for the MILP model is only 237 s, which is very low compared to the MINLP model. In other word, the non-linear problem includes high calculation time [61–65]. Consequently, according to the values of power difference and amplitude and voltage angle as well as the calculation time, it can be said that the mentioned calculation error was ignored due to the very low calculation time of the MILP model. Consequently, the MILP model is a suitable model to replace the MINLP model.

B) *Evaluating the location of charging stations*: In this section, the optimal locations of charging stations are evaluated, and the corresponding results are shown in Table 2. We assumed that the cost of charging stations plus microturbines is equal to 100,000 $ [66]. According to the Table 2 results, nine charging stations are built in the network, which are located on buses 8, 10, 17, 32, 39, 42, 48, 50, and 55. By comparing Fig. 2 and Table 2, we conclude that there is a charging station in all feeders. The reason is that during the hours when electric vehicles are not in the charging stations, they deliver power back to the grid through a microturbine. Hence, they are commonly fed on the spot, and the bus voltage will be close to one p.u. That is, the third part of the objective function becomes very minimal. Therefore, to reduce the amount of voltage deviation and energy cost, the arrangement of charging stations in the network is such that they are in all feeders.

C) *Evaluating network indicators*: In this section, we evaluated the changes in network indicators due to the entry of charging stations. Also, we carried out several different studies to check the network indicators, which are as follows:

- **Case 1**: Carrying out load distribution in the test case distribution network. In other words, there is no charging station, and it is our base case.
- **Case 2**: Locating charging stations in the desired distribution network, assuming only the charging mode for EVs.
- **Case 3**: Locating charging stations in the desired distribution network, assuming charging and discharging modes for EVs.

The results of this section are demonstrated in Table 3. It shows the maximum voltage drop and maximum overvoltage during the peak hour for study cases 1 to 3. Based on this figure we can see that in study case 1, the voltage deviations of the buses are high relative to each other. So, the lowest voltage is equal to 0.908p.u. But in case studies 2 and 3, the voltage changes of the buses are very low compared to one p.u. In other words, in the second and third study cases the voltage profile is flatter or smoother. Therefore, the presence of charging stations with microturbine power supply will significantly improve the voltage profile. Because the loads are fed by the charging station's microturbine at the consumption place. Eventually, the network's voltage drop is considerably reduced, and following that, the bus voltage will be close to one p.u. In addition to the scenarios discussed, the assumption of the discharge mode doesn't have numerous changes on the network indicators in case 2. In other words, the voltage profiles of the second and third case studies are very close to each other. Hence, case 2 can be appropriate for our research.

Table 1
Comparison of the Results for MINLP and MILP Models.

Parameter	MINLP	MILP	% Calculation Error
Active Power of Upstream Network at Peak Load Time (p.u.)	0.42	0.408	2.93
Reactive Power of Upstream Network at Peak Load Time (p.u.)	2.34	2.19	2.51
Mean of Voltage Magnitude (p.u.)	0.991	0.992	0.51
Mean of Voltage Angle (rad.)	−0.008	−0.00832	0.39
Number of EVs Stations	9	9	0
Calculation Time (sec.)	4751	237	95.01

Table 2
Location of charging stations.

Charging Station	Feeder	Location (Bus)
1	1–27	8
2	1–27	10
3	1–27	17
4	28–35	32
5	36–46	39
6	36–46	42
7	47–50	48
8	49–50	50
9	53–65	55

Table 3
Comparison of Voltage Drop, Overvoltage, and Energy Loss across Different Cases.

Case	Maximum Voltage Drops (p.u.)	Maximum Overvoltage (p.u.)	Energy Loss (p.u.)
1	0.092	0	2.08
2	0.037	0.01	1.23
3	0.036	0.01	1.21

Table 3 shows the network energy losses across different study cases. As apparent, the energy loss in the first case is very high. The reason is that all loads are fed by the upstream network, and since there is a distance between the loads and the feeders, energy loss will be high. But we should note that in the second and third case studies, energy losses are much lower than in case 1. Because in cases 2 and 3, the charging station's microturbine feeds the loads in most hours. Consequently, energy losses will be very low. Also, considering the discharge mode of electric vehicles won't have a significant impact on the study case.

D) *Evaluating different parts of the objective function*: In this section, the amount of voltage deviation, energy cost [67–69], and the cost of constructing charging stations for the case studies that only consider the charging mode of electric vehicles are discussed. As can be seen in Table 4, the cost of building charging stations is 900,000 US dollars. As previously mentioned, nine charging stations are built in the network, and the cost of building each station was 100,000 $. Consequently, the total cost of building charging stations will be 900,000 dollars. It should be noted that the cost of energy in this case is 433.814 dollars. If the charging station is not available in the network, the amount of energy cost according to [51] will be 1425 dollars. So, with the presence of charging stations and microturbine power supply in the mentioned distribution network, the amount of energy cost is reduced significantly. This is because they have received power from a cheaper source several times, and the energy losses have been greatly reduced. Hence, the cost of energy will be reduced compared to the base case. The last variable that is checked in Table 4 is voltage deviation, which is equal to 1.142p.u. in our studies. But it should be noted that this case is equal to 43.8 based on [52]. Therefore, the charging station supplied by the microturbine power source will greatly reduce the voltage deviation.

5. Conclusion

In this paper, we discussed the optimal placement of EV charging stations in the distribution network. We not only minimized the cost of building charging stations but also did the same for the cost of energy as well as voltage deviations. The original problem was bound to the equations of optimal AC power distribution and the operating model of EVs and charging stations. That's why the mentioned problem had a MINLP format. So, we transformed it into a MILP problem under certain assumptions. Ultimately, by applying the proposed problem to the 69-bus distribution network, we obtained the following results:

- Construction of charging stations in the distribution network feeders to achieve a smoother voltage profile and lower energy losses.
- Improving the distribution network voltage profile, reducing energy losses and energy costs in the presence of charging stations supplied by microturbine power in the grid.
- Achieving high execution speed by leveraging the MILP model for the proposed problem compared to the original MINLP configuration.
- Achieving low computational error by implementing the MILP approach for the proposed problem compared to the original model.

In this study, we adopt a linearized power flow model that assumes voltage magnitudes are approximately 1p.u. and that the voltage angle deviation between the sending and receiving ends of each distribution line is less than 6 degrees. These assumptions, supported by previous research [24,33,45], may not hold in all real distribution networks; hence, future work will explore alternative linearization techniques for improved accuracy.

Table 4
Objective function values for different parts.

Index	Value
Voltage Deviation (p.u.)	1.142
Energy Cost ($)	814.433
Investment Cost ($)	900,000

CRediT authorship contribution statement

Mehdi Veisi: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Hossein Naderian:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Formal analysis, Data curation. **Mazaher Karimi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The research presented in the paper was develop within the project "Best4Grid – Vehicle battery storage for green transport and grid stability in the Nordics", which is part of the Nordic Grand Solutions Programme funded by Nordic Energy Research.

Data availability

Data will be made available on request.

References

[1] Navesi RB, et al. Reliable operation of reconfigurable smart distribution network with real-time pricing-based demand response. *Electr Pow Syst Res* 2025;241:111341.
[2] Pirouzi S, Aghaei J, Niknam T, Khooban MH, Dragicevic T, Farahmand H, et al. Power conditioning of distribution networks via single-phase electric vehicles equipped. *IEEE Syst J* 2019;13(3):3433–42.
[3] Kisacikoglu MC, Ozpineci B, Tolbert LM. EV/PHEV Bidirectional Charger Assessment for V2G Reactive Power Operation. *IEEE Trans Power Electron* 2013;28(12):5717–27.
[4] Wang R, et al. Stochastic economic sizing of hydrogen storage-based renewable off-grid system with smart charge of electric vehicles according to combined hydrogen and power model. *J Storage Mater* 2025;108:115171.
[5] Zhang J, et al. Eco-power management system with operation and voltage security objectives of distribution system operator considering networked virtual power plants with electric vehicles parking lot and price-based demand response. *Comput Electr Eng* 2025;121:109895.
[6] S. Shafiee, M. Fotuhi-Firuzabad, M. Rastegar, M., "Impacts of controlled and uncontrolled PHEV charging on distribution systems," *9th IET International Conference on Advances in Power System Control, Operation and Management (APSCOM 2012)*, pp. 1- 6, 2013.
[7] Luo X, Chan KW. Real-time scheduling of electric vehicles charging in low-voltage residential distribution systems to minimise power losses and improve voltage profile. *IET Gener Transm Distrib* 2014;8(3):516–29.
[8] Nafisi H, Agah SMM, Askarian Abyaneh H, Abedi M. Two-stage optimization method for energy loss minimization in microgrid based on smart power management scheme of PHEVs. *IEEE Trans Smart Grid* 2015;12(99):1–9.
[9] Cheng L, Chang Y, Huang R. Mitigating Voltage Problem in Distribution System with Distributed Solar Generation Using Electric Vehicles. *IEEE Trans Sustainable Energy* 2015;6(4):1475–84.
[10] Kavousi-Fard A, Niknam T, Fotuhi-Firuzabad M. Stochastic reconfiguration and optimal coordination of V2G plug-in electric vehicles considering correlated wind power generation. *IEEE Trans Sustainable Energy* 2015;6(3):822–30.

[11] Abdelsamad SF, Morsi WG, Sidhu TS. Impact of wind-based distributed generation on electric energy in distribution systems embedded with electric vehicles. *IEEE Trans Sustainable Energy* 2015;6(1):79–87.
[12] Wu CX, Chung CY, Wen FS, Du DY. Reliability/cost evaluation with PEV and wind generation system. *IEEE Trans Sustainable Energy* 2014;5(1):273–81.
[13] Sortomme E, Hindi MM, MacPherson SJ, Venkata SS. Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses. *IEEE Trans On Smart Grid* 2011;2(1):198–205.
[14] Wang J, Liu C, Ton D, Zhou Y, Kim J, Vyas A. Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power. *Energy Policy* 2011;39(7):4016–21.
[15] Galus MD, Koch S, Andersson G. Provision of load frequency control by PHEVs, controllable loads, and a cogeneration unit. *IEEE Trans On Ind Electron*, 2011;58 (10):4568–82.
[16] Long H, Guo Z, Zhou C. A charge-discharge optimization strategy considering the spatiotemporal distribution of electric vehicles and the operational safety of the power distribution network in the power-transportation coupling network. *J Clean Prod* 2024;452.
[17] Tang J, Ji G-Q, Liu Z, Sheu J-B. Electric vehicle battery-charging service and operations managing under different charging station construction modes. *Transportation Research Part E: Logistics and Transportation Review* 2024;181.
[18] Cabrera-Tobar, Ana, Nicola Blasuttigh, Alessandro Massi Pavan, and Giovanni Spagnuolo. "Demand response of an Electric Vehicle charging station using a robust-explicit model predictive control considering uncertainties to minimize carbon intensity." *Sustainable Energy, Grids and Networks* 38, 2024.
[19] Xu H, Miao S, Zhang C, Shi D. Optimal placement of charging infrastructures for large-scale integration of pure electric vehicles into grid. *Int J Electr Power Energy Syst* 2013;53:159–65.
[20] Alhazmi YA, Mostafa HA, Salama MMA. Optimal allocation for electric vehicle charging stations using Trip Success Ratio. *Int J Electr Power Energy Syst* 2017;91: 101–16.
[21] Chakraborty P, Pal M. Planning of fast charging infrastructure for electric vehicles in a distribution system and prediction of dynamic price. *Int J Electr Power Energy Syst* 2024;155.
[22] Hosseini S, Sarder MD. Development of a Bayesian network model for optimal site selection of electric vehicle charging station. *Int J Electr Power Energy Syst* 2019; 105:110–22.
[23] Wang C, Dunn R, Robinson F, Lian Bo, Yuan W, Redfern M. Active–reactive power approaches for optimal placement of charge stations in power systems. *Int J Electr Power Energy Syst* 2017;84:87–98.
[24] Naghibi AF, et al. Stochastic economic sizing and placement of renewable integrated energy system with combined hydrogen and power technology in the active distribution network. *Sci Rep* 2024;14(1):28354.
[25] Jiang W, et al. Optimal economic scheduling of microgrids considering renewable energy sources based on energy hub model using demand response and improved water wave optimization algorithm. J Storage Mater 2022;55:105311.
[26] Dehghani M, et al. Blockchain-based securing of data exchange in a power transmission system considering congestion management and social welfare. Sustainability 2020;13(1):90.
[27] Yuan Z, et al. Probabilistic decomposition-based security constrained transmission expansion planning incorporating distributed series reactor. IET Gener Transm Distrib 2020;14(17):3478–87.
[28] Yu D, Ghadimi N. Reliability constraint stochastic UC by considering the correlation of random variables with Copula theory. IET Renew Power Gener 2019; 13(14):2587–93.
[29] Eslami, Mahdiyeh, et al. "A new formulation to reduce the number of variables and constraints to expedite SCUC in bulky power systems." Proceedings of the national academy of sciences, india section a: physical sciences 89 (2019): 311-321.
[30] Nejad HC, et al. Reliability based optimal allocation of distributed generations in transmission systems under demand response program. Electr Pow Syst Res 2019; 176:105952.
[31] Ghiasi M, et al. Enhancing Power Grid Stability: Design and Integration of a Fast Bus Tripping System in Protection Relays. IEEE Trans Consum Electron 2024.
[32] Khodaei H, et al. Fuzzy-based heat and power hub models for cost-emission operation of an industrial consumer using compromise programming. Appl Therm Eng 2018;137:395–405.
[33] Akbari E, et al. Multi-objective economic operation of smart distribution network with renewable-flexible virtual power plants considering voltage security index. *Sci Rep* 2024;14(1):19136.
[34] Ghadimi N, et al. An innovative technique for optimization and sensitivity analysis of a PV/DG/BESS based on converged Henry gas solubility optimizer: A case study. IET Gener Transm Distrib 2023;17(21):4735–49.
[35] Zhu L, et al. Multi-criteria evaluation and optimization of a novel thermodynamic cycle based on a wind farm, Kalina cycle and storage system: an effort to improve efficiency and sustainability. Sustain Cities Soc 2023;96:104718.
[36] Liu J, et al. An IGDT-based risk-involved optimal bidding strategy for hydrogen storage-based intelligent parking lot of electric vehicles. J Storage Mater 2020;27: 101057.
[37] Cai W, et al. Optimal bidding and offering strategies of compressed air energy storage: A hybrid robust-stochastic approach. Renew Energy 2019;143:1–8.
[38] Pu JH, Li Y, Li RC, Hua N, Zhang H, Lu Y, et al. Zhang X-K, Design and performance of a compact lightweight hybrid thermal management system using phase change material and liquid cooling with a honeycomb-like structure for prismatic lithium-ion batteries. J Power Sources 2024;624:235632.
[39] Li W, Xie Y, Hu X, Zhang B, Fowler M, Panchal S, et al. An efficient two-stage heating strategy for embedded heat pipe system considering power and energy requirements from battery, Applied Thermal Engineering, Volume 257. Part C 2024;124499.
[40] Ma W, Xie Y, Guo S, Li W, Yang R, Panchal S, et al. A mechanism-data driven resistance transfer algorithm for lithium-ion batteries and its application to thermal modeling. Journal of Energy Storage, Volume 102, Part A 2024;114066.
[41] Liu S, Wang Y, Liu Q, Panchal S, Zhao J, Fowler M, et al. Thermal equalization design for the battery energy storage system (BESS) of a fully electric ship. Energy December 2024;312(15):133611.
[42] Chen J, Kollmeyer P, Panchal S, Masoudi Y, Gross O, Emadi A. Experimental Results of Battery Power Capability Measurement on Cells with Different State of Health Levels. In: 2024 IEEE Transportation Electrification Conference and Expo (ITEC); 2024. p. 1–6.
[43] A Afzal, D Thakur, AR Kaladgi, S Panchal, C Saleel, "A. Influence of the Fly Ash Material Inoculants on the Tensile and Impact Characteristics of the Aluminum AA 5083/7.5 SiC Composites. Materials 2021, 14, 2452", s Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations, 2021.
[44] Suryavanshi, shweta sayajirao and Ghanegaonkar, pravin mahadev and Panchal, Satyam, Enhancing Efficiency in Air-Cooled Cylindrical Battery Temperature Management Systems for Electric Vehicles: A Cfd Analysis of a Novel Uniform Flow Distribution Plate. Available at SSRN: https://ssrn.com/abstract=4888691 or https://doi.org/10.2139/ssrn.4888691.
[45] Norouzi M, et al. Risk-averse and flexi-intelligent scheduling of microgrids based on hybrid Boltzmann machines and cascade neural network forecasting. *Appl Energy* 2023;348:121573.
[46] Li S, et al. Evaluating the efficiency of CCHP systems in Xinjiang Uygur Autonomous Region: an optimal strategy based on improved mother optimization algorithm. Case Stud Therm Eng 2024;54:104005.
[47] Guo X, Ghadimi N. Optimal design of the proton-exchange membrane fuel cell connected to the network utilizing an improved version of the metaheuristic algorithm. Sustainability 2023;15(18):13877.
[48] Yuan K, et al. Optimal parameters estimation of the proton exchange membrane fuel cell stacks using a combined owl search algorithm. Energy Sources Part A 2023;45(4):11712–32.
[49] Han E, Ghadimi N. Model identification of proton-exchange membrane fuel cells based on a hybrid convolutional neural network and extreme learning machine optimized by improved honey badger algorithm. Sustainable Energy Technol Assess 2022;52:102005.
[50] Zhang J, Khayatnezhad M, Ghadimi N. Optimal model evaluation of the proton-exchange membrane fuel cells based on deep learning and modified African Vulture Optimization Algorithm. Energy Sources Part A 2022;44(1):287–305.
[51] Yao M, et al. Stochastic economic operation of coupling unit of flexi-renewable virtual power plant and electric spring in the smart distribution network. *IEEE Access* 2023.
[52] Zadehbagheri M, Dehghan M, Kiani M, Pirouzi S. Resiliency-constrained placement and sizing of virtual power plants in the distribution network considering extreme weather events. *Electr Eng* 2024:1–17.
[53] Oboudi MH, Hamidpour H, Zadehbagheri M, Safaee S, Pirouzi S. Reliability-constrained transmission expansion planning based on simultaneous forecasting method of loads and renewable generations. *Electr Eng* 2024:1–21.
[54] Pirouzi S, Zadehbagheri M, Behzadpoor S. Optimal placement of distributed generation and distributed automation in the distribution grid based on operation, reliability, and economic objective of distribution system operator. *Electr Eng* 2024: 1–14.
[55] Zadehbagheri M, Kiani MJ, Pirouzi S, Movahedpour M, Mohammadi S. The impact of sustainable energy technologies and demand response programs on the hub's planning by the practical consideration of tidal turbines as a novel option. *Energy Rep* 2023;9:5473–90.
[56] Norouzi, M., Aghaei, J., & Pirouzi, S. (2019, September). Enhancing distribution network indices using electric spring under renewable generation permission. In *2019 International Conference on Smart Energy Systems and Technologies (SEST)* (pp. 1-6). IEEE.
[57] Bagherzadeh L, Shayeghi H, Pirouzi S, Shafie-khah M, Catalão JP. Coordinated flexible energy and self-healing management according to the multi-agent system-based restoration scheme in active distribution network. *IET Renew Power Gener* 2021;15(8):1765–77.
[58] Shahbazi A, Aghaei J, Pirouzi S, Niknam T, Vahidinasab V, Shafie-khah M, et al. Holistic approach to resilient electrical energy distribution network planning. *Int J Electr Power Energy Syst* 2021;132:107212.
[59] Norouzi M, Aghaei J, Pirouzi S, Niknam T, Fotuhi-Firuzabad M, Shafie-khah M. Hybrid stochastic/robust flexible and reliable scheduling of secure networked microgrids with electric springs and electric vehicles. *Appl Energy* 2021;300: 117395.
[60] Generalized Algebraic Modeling Systems (GAMS). [Online]. Available: http://www.gams.com.
[61] Mahdinia S, et al. Optimization of PEMFC model parameters using meta-heuristics. Sustainability 2021;13(22):12771.
[62] Azar K, Keyvan, et al. Developed design of battle royale optimizer for the optimum identification of solid oxide fuel cell. Sustainability 2022;14(16):9882.
[63] Saeedi M, et al. Robust optimization based optimal chiller loading under cooling demand uncertainty. Appl Therm Eng 2019;148:1081–91.
[64] Hamian M, et al. A framework to expedite joint energy-reserve payment cost minimization using a custom-designed method based on mixed integer genetic algorithm. Eng Appl Artif Intel 2018;72:203–12.

[65] Cao Y, et al. Optimal operation of CCHP and renewable generation-based energy hub considering environmental perspective: An epsilon constraint and fuzzy methods. Sustainable Energy Grids Networks 2019;20:100274.
[66] Li X, Lopes LA, Williamson SS. On the suitability of plug-in hybrid electric vehicle (PHEV) charging infrastructures based on wind and solar energy. PES: IEEE Power & Energy Society General Meeting; 2009. p. 1–8.
[67] Veisi M, Adabi F, Kavousi-Fard A, Karimi M. A Framework of Electricity Market Based on Two-Layer Stochastic Power Management for Microgrids. IEEE Access 2022;10:41047–63.
[68] Baziar A, Bo R, Ghotbabadi MD, Veisi M, Ur Rehman W. Evolutionary Algorithm-Based Adaptive Robust Optimization for AC Security Constrained Unit Commitment Considering Renewable Energy Sources and Shunt FACTS Devices. IEEE Access 2021;9:123575–87.
[69] Veisi, Mehdi, Farid Adabi, Abdollah Kavousi-Fard, and Mazaher Karimi. "A novel comprehensive energy management model for multi-microgrids considering ancillary services." *IET Generation, Transmission & Distribution* 16, pp. 4710-4725, no. 23, 2022.