IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 5 May 2024, accepted 25 June 2024, date of publication 28 June 2024, date of current version 9 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3420706

RESEARCH ARTICLE

Economic Management of an Intelligent Parking Lot Using a Time-Based Load Response Program

MAJID VALIZADEH[1], FARSHAD MORADI[1], AMIRHOSSEIN KHOSRAVI SARVENOEE[1], MOHAMMAD KOHZADIPOUR[1], N. GOWTHAM[2], (Senior Member, IEEE), AND KAREEM M. ABORAS[3]

[1]Department of Electrical Engineering, Ilam University, Ilam 69316-47574, Iran
[2]Department of Electrical and Electronics Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, Karnataka 576104, India
[3]Electrical Power and Machines Department, Faculty of Engineering, Alexandria University, Alexandria 21544, Egypt

Corresponding author: N. Gowtham (gowtham.n@manipal.edu)

ABSTRACT The importance of intelligent parking lots has increased with the smarter power grids and the addition of vehicle technology to the grid on electric cars. Intelligent parking lots have many features requiring an innovative and optimal energy management program to benefit from. Therefore, providing a comprehensive and optimal model for energy management of electric car parking lots in intelligent networks is one of the basic needs of the owners and operation of electric car parking lots. According to this issue, this paper presents a comprehensive model for more optimal use of bright parking lots. In this model, to participate more optimally in the next-day market, an artificial neural network is first trained to predict the overall demand for parking charges and the number of cars in the parking lot every hour of the next day. In continuation of the problem of parking participation planning in the day-ahead market, the real-time market and the intelligent charging/discharging of cars have been formulated simultaneously. The proposed model provides the possibility of predicting parking lot charging demand using a neural network, participation in the day-ahead market and balance market, and the possibility of using the ability to discharge electric cars for the parking lot operator. This model is formulated as a mixed correct linear programming to maximize the profit of the parking garages. In the proposed method, the algorithm performs fast calculations, and this method also has the ability to be implemented practically. The simulation results demonstrate that the suggested approach could boost intelligent parking's profit significantly.

INDEX TERMS Smart parking, artificial network, load response program, economic management.

I. INTRODUCTION

In the coming years, with the increase in the number of electric cars, the number of parking lots will also increase. In such a situation, parking lots must consider electric car owners' benefits in their plans. Providing profit to the owners of electric cars will encourage them to use the desired parking lot again. Therefore, in continuation of this work and to make the proposed model more comprehensive, the problem can be modelled and solved by combining the profit of parking and electric car owners. This work can eventually lead to more use of intelligent parking lots and ultimately increase their profits [1], [2], [3], [4].

Integrating electric vehicles in distribution networks can increase peak load, energy losses, and voltage drop. The adverse effects that electric cars create in distribution networks depend on the charging they use. Uncontrolled charging of electric vehicles causes an increase in the peak load of the network and a severe voltage drop. However, if the charging of electric cars is controlled, since the load of electric cars is distributed at different hours of the day, the occurrence of a severe peak load in the network is avoided.

The associate editor coordinating the review of this manuscript and approving it for publication was Shadi Alawneh.

© 2024 The Authors. This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License.
For more information, see https://creativecommons.org/licenses/by-nc-nd/4.0/

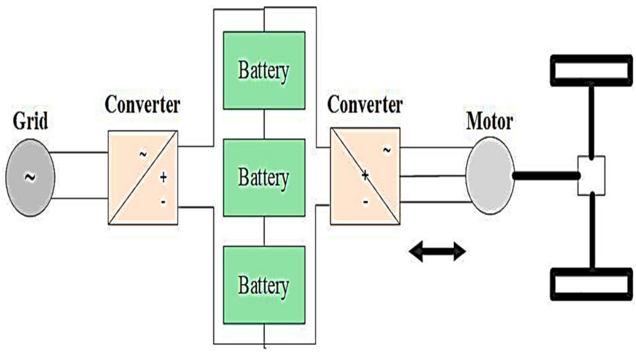


FIGURE 1. Internal structure of the all-electric car.

Therefore, the unplanned presence of electric vehicles in distribution networks and the absence of a correct demand management program can disrupt the operation of distribution networks [5], [6], [7]. Figure 1 shows the internal structure of the all-electric car.

One of the most essential features of electric cars is their flexibility in connecting to power grids. With the development of electric cars, a new type of electric load is added to the power grid, on the other hand, electric car batteries act as energy storage sources. In this way, when the grid load is low, and the energy price is low, they receive electrical energy from the grid and sell it to the energy grid during peak load. During low load hours of the network, when the production rate of power plant units is lower than their nominal capacity, the efficiency of the units decreases, and also, the continuous stop and start of production units and changes in their production rate cause wear and tear and reduce the life of the equipment. Therefore, using electric vehicles to receive energy during off-peak hours improves the state of the power system both technically and economically. However, owners of these cars may benefit greatly from the use of electric vehicles and their discharge in distribution networks during peak electricity consumption, which is caused by the use and operation of production units that are highly polluting and have low efficiency [8], [9], [10].

A. LITERATURE REVIEW

In [11], a coordinated distribution strategy of electric vehicles (EVs) is used to smooth out the production power caused by renewable energy sources and microgrid load fluctuations. In addition to meeting the demands of logistical distribution chores, the suggested design aims to decrease the total cost of microgrid operation. Also, this method presents a self adaptively Imperialist Competitive Algorithm (SaICA) to solve the proposed model. In [12], the batteries of EVs in a parking lot are used to store energy in a microgrid. This approach considers a two-stage stochastic model for the microgrid's energy management coupled to the upstream network. A heterogeneous continuous time Markov chain is suggested to represent the changing parking capacity. Additionally, the Benders decomposition approach is used to solve this model. In [13], a new frequency support strategy is introduced to control the performance of DES and controllable loads, i.e., EVs. In this method, EV batteries with a droop controller, communication links, and improved feedback mechanisms are used as modified droop controllers (MDCs). Also, an aggregator(AG) is provided to coordinate the fleet of EVs. In [14], it investigates optimal energy management in the structure of microgrids based on renewable energy sources in the presence of grid-connected electric vehicles (PEV). This method is equipped with a parking lot to control and collect PEVs. The issue of placing wind power plants in contemporary structures with sizable parking areas for EV charging is looked at in [15].

Since the charging demand of electric vehicles usually does not correspond to the power fluctuations of wind power plants, the Markov decision process (MDP) is used to formulate EV charging with wind power. Also, the method based on distributed simulation is used for optimal charging. In [16], it investigates the economic optimization of the performance of a low-voltage smart microgrid, including electric vehicles (EVs) connected to the grid that uses the Harmony Search Algorithm to control the charging of EVs. In this method, the random parameters include loads, renewable energy sources, and the driving pattern of EVs. In [17], a predictive control algorithm is proposed for the economic optimization of a microgrid, including electric vehicle charging stations. The proposed algorithm manages the purchase and sale of energy with the upstream network, manages the use of energy storage devices, and maximizes the use of renewable energy sources. Also, system modeling has been done using the Energy Hubs method in this method. In [18], energy management and optimal operational strategies of electric vehicles (EVs) and Battery Swapping Stations (BSS) in smart microgrids are introduced due to the effects of uncoordinated charging of EVs and BSS. This method's main optimization problems are cost and profit maximization. A multi-objective algorithm is presented in [19] for the best distribution of grid-connected hybrid electric vehicle (PHEV) parking lots and renewable energy sources. The suggested method establishes the quantity, position, and dimensions of RES and parking lots, as well as the energy-related time of each source. Under this approach, the artificial bee colony (ABC) algorithm is utilized to solve the system cost reduction problem, which is regarded as an optimization problem. Table 1 looks at the strategies that have been investigated and contrasts them with the suggested approach. In [20], a new model of an energy management system is presented, which uses a new hybrid algorithm for microgrid energy management. This hybrid algorithm includes multi objective particle swarm optimization (MOPSO) and the Harmony Search Algorithm (HS). In [21], optimal energy management of distributed energy resources and parking of electric vehicles is presented, which includes inherent uncertainties in the output. In [22], a flexible microgrid planning and optimization problem is proposed using meta-heuristic algorithms that model the uncertainties of the problem. In [23], an optimal design of intelligent and combined hydrogen, heat and power meters in the active system has been proposed, which reduces the voltage and minimizes the total planning costs by using different scenarios. In order to minimize the system costs of the distribution network and the cost of battery discharge from the presented electric vehicles in [24], a smart electric vehicle charging strategy with limited chance in the microgrid is proposed. In order to provide a reliable power balance for microgrid operation, in [25], a dynamic control system based on Fuzzy-Sparrow Search Algorithm (SSA) is proposed.

In general, the main advantage of the proposed model in this work is that it simultaneously provides the following capabilities:

- participate more optimally in the next-day market
- predict the overall demand for parking charges
- predict the number of cars in the parking lot every hour of the next day
- planning in the day-ahead market
- the real-time market
- the intelligent charging/discharging of cars
- Quickly perform algorithm calculations and improve response speed
- Ability to implement the proposed method in a practical way

This research presents an energy management system for electric vehicles in parking lots and examines its practical constraints. Multiple electric cars can be scheduled and managed by the model that is being provided. This approach aims to maximize parking profits, ensure that transactions between the distribution system operator, vehicle owners, and parking operator are transparent, and increase car owners' happiness. The profit function will be optimized once the entire daily expenditures and parking income are modeled to maximize the parking profit.

II. PROBLEM MODELING

In this section, a stochastic model is proposed to model the behavior of electric vehicles. This approach generates several scenarios for the driving behaviors of electric vehicles, such as when the vehicle enters the parking lot, when it exits, and how charged the battery is when it enters the lot. The process for forecasting the demand for parking fees and the number of vehicles in the lot the next day is described below. Finally, using the scenarios obtained for the characteristics of electric vehicles and the predictions made by the neural network, the problem of optimal planning of intelligent electric vehicle parking has been formulated, and its solution method has been described.

A. MODELING THE BEHAVIOR OF ELECTRIC VEHICLES

It is vital to randomly take into account each EV owner's characteristics, such as the time the EV enters and exits the parking lot, the initial state of charge of the EV upon entry, and the battery capacity of the vehicles, in order to develop an accurate model for the parking behavior of electric vehicles. The quantity of SOC at the time of entry and departure and the timing of entry are often determined using the truncated Gaussian distribution function to simulate the uncertainty of the behavior of owners of electric cars [26]. Stated differently, for every EV, three random numbers the EV entry time into the parking lot, the EV leave time from the parking

TABLE 1. Review of the studied methods and their comparison with the proposed method.

References	Advantage	Disadvantage
[11]	Fast charging time and regular electric vehicle charging/discharging strategy	Low efficiency
[12]	Reducing the total operating cost of the microgrid	Low operating quality
[13]	Frequency stabilization	System complexity
[14]	Improving the charging process of PEVs	Low operating quality
[15]	Good performance of HSBPI in charging cost reduction and scalability	Failure to consider other basic loads of the building
[16]	Proper performance in the presence of random parameters in the network	High pollution
[17]	Management of electric vehicle charging and load demand	System complexity
[18]	Reducing adverse effects caused by inconsistent charging of EVs	Low operating quality
[19]	Minimizing the total energy cost of the system	Low efficiency
[20]	Increasing the penalty for the cost of not supplying energy and the costs of the demand response program	System complexity
[21]	Increasing technical and economic performance	Not considering the electric car model tariff
[22]	Improving microgrid flexibility	High cost
[23]	Reducing voltage and minimizing planning costs	Low operating quality
[24]	Reduce system costs	System complexity
[25]	Providing constant power regardless of production differences	High cost
This paper	Prediction of parking charge demand using neural network	Failure to model the integration of parking profits and electric car owners

lot, and the EV's initial state of charge upon entering—are produced using a truncated Gaussian distribution. Generating random numbers will persist until all available parking spaces are occupied. The parking lot's automobile space limitations are considered while creating random numbers. The process above has to be performed to generate each of the scenarios.

To generate EV scenarios, the behavior of each EV is modeled using equations 1 to 4 [27]. Equation 1 is used to generate the scenarios of the arrival time of each electric car in the parking lot, considering the Gaussian distribution cut with the mean value μ_{arv}, standard deviation σ_{arv}, the lower limit equivalent to the minimum arrival time $t_n^{arv,min}$ and the upper limit equivalent to the maximum arrival time $t_n^{arv,max}$, Used. Equation 2 ensures that the generated scenarios are reasonable. Therefore, the lower limit of the exit time of each EV is equal to $Max(t_n^{dep,min}, t_n^{arv})$ so that the exit time from the parking lot is not earlier than the entry time. Based on this, the cut area is considered for generating scenarios of the time of leaving the parking lot according to equation 3. Also, the SOC of each EV at the time of entering the parking lot is obtained according to equation 4.

$$\mathrm{t_i^{arv}} = \mathrm{f_{TG}}(\mathrm{x}; \mu_{\mathrm{arv}}, \sigma^2_{\mathrm{arv}}, (\mathrm{t_i^{arv,min}}, t_i^{arv,max}) \tag{1}$$

$$t_i^{arv} \leq t_i^{dep} \tag{2}$$

$$\mathrm{t_i^{dep}} = \mathrm{f_{TG}}(\mathrm{x}; \mu_{\mathrm{dep}}, \sigma^2_{\mathrm{dep}}, \max(\mathrm{t_i^{dep,min}}, t_i^{arv}) \tag{3}$$

$$\mathrm{SOC^{EV}_{i,t_i^{arv}}} = \mathrm{f_{TG}}(\mathrm{x}; \mu_{\mathrm{soc}}, \sigma^2_{\mathrm{soc}}, (\mathrm{soc_i^{min}}, soc_i^{max}) \tag{4}$$

Based on relationships 1 to 4, the SOC value of each EV that arrived at the parking lot at time t_i^{arv} and left the parking lot at time t_i^{dep}, without considering the energy exchange in the parking lot, can be expressed as equation 5. Also, the total number of cars that entered the parking lot at the time t_i^{arv} and left the parking lot at the time t_i^{dep} is calculated by equation 6.

$$\mathrm{SOC^{EV}_{i,t}} = \begin{cases} \mathrm{SOC_i^{EV}} & \mathrm{t_i^{arv}} \leq \mathrm{t} \leq \mathrm{t_i^{dep}} \\ 0 & \text{Otherwise} \end{cases} \tag{5}$$

$$\mathrm{N^{EV}_{t^{arv},t^{dep}}} = \sum_{\mathrm{i=1}}^{\mathrm{Nev}} \mathrm{EV_{i,t}} \quad \mathrm{t_i^{arv}} \leq \mathrm{t} \leq \mathrm{t_i^{dep}} \tag{6}$$

In these equations, $N^{EV}_{t^{arv},t^{dep}}$ is the total number of cars that have entered the parking lot during the time interval between t_i^{arv} and t_i^{dep}. Based on the above relationships, the number of cars entering, the number of cars leaving, and the number of cars in the parking lot at time t are determined based on equations 7 to 9, respectively. Equation 10 also guarantees that the number of parked cars is not greater than the number of empty car spaces in the parking lot.

$$\mathrm{N_t^{arv}} = \sum_{\mathrm{i}}^{\mathrm{Nev}} \{\mathrm{EV_i}; \mathrm{t_i^{arv}} = \mathrm{t}\} \tag{7}$$

$$\mathrm{N_t^{dep}} = \sum_{\mathrm{i}}^{\mathrm{Nev}} \{\mathrm{EV_i}; \mathrm{t_i^{dep}} = \mathrm{t}\} \tag{8}$$

$$\mathrm{N_t^{P}} = \mathrm{N_{t-1}^{P}} + \mathrm{N_t^{arv}} - \mathrm{N_t^{dep}} \tag{9}$$

$$\mathrm{N_t^{P}} \leq \mathrm{N^{P,max}} \tag{10}$$

Each car's capacity is determined by the type of battery it uses. Twenty-four battery classifications for various kinds of electric cars are mentioned in [28]. The probability distribution of capacities in each EV class is taken to be in order to reflect the uncertainty surrounding the battery capacity of electric vehicles in the parking lot [28].

B. PARKING BEHAVIOR MODELING

In this section, an artificial neural network (ANN) is used to model the behavior of an intelligent parking operator. In this method, using a neural network, the parking operator predicts the charging demand of cars the next day and the number of cars in the parking lot every hour. The parking lot operator delivers a part of the charge demand needed by the cars from the day-ahead market and participates in the day-ahead market based on this estimate. To compensate for the changes in car charging demand due to the unpredictable behavior of cars, two strategies of buying and selling energy in the spot market (balanced market), unloading cars in the parking lot and recharging them in hours, are used.

The multilayer perceptron (MLP) network has a feed-forward structure and uses the error back-propagation method to learn the network. This is considered a monitored network. In other words, to train this network, in addition to the training data (network input), the correct output must also be taught to the system. According to Kolmogorov's theorem, an MLP network with three layers can learn and solve any linear and non-linear problem [28]. Figure 2 shows the structure of a four-layer perceptron network. The goal is to train an MLP neural network to predict the hourly charging demand of all cars in the parking lot and the number of cars in the parking lot each hour from the day's network for the next day. For this purpose, the parking information of electric cars in the past few years can be used.

Typically, in an intelligent parking lot, car information such as entry time, exit time, charging amount, and also the number of cars connected to charging is stored every hour. Using data stored for several years for different parking lots, a suitable neural network can be trained to predict charging demand and the number of cars in the parking lot. Neural network inputs should be considered as parameters affecting the charging demand of electric vehicles. The most important of these parameters can be the hours of the day, days of the year, and the capacity of the innovative park. It is possible to predict the total parking fee demand and the number of cars in the parking lot every hour by considering the specified parameters as input to the neural network. As a result, Figure 3 shows the neural network designed to predict the behavior of intelligent parking.

Figure 3 shows that the neural network's inputs include the hour of the day T, the day of the year d, and the capacity of the Npark intelligent parking lot. The total parking fee demand per hour (Pdemand) and the number of automobiles in the parking lot per hour (Nev) are further outputs of the neural

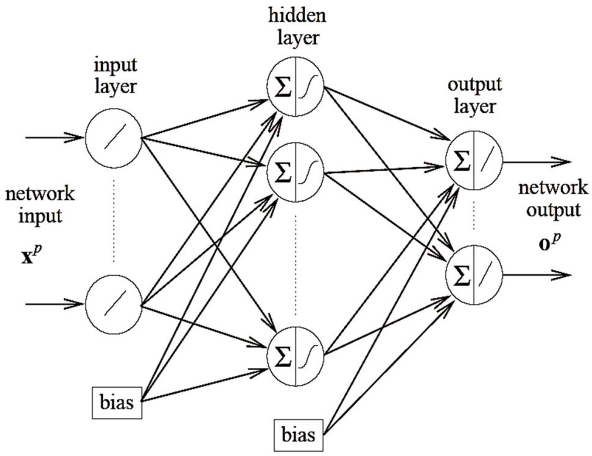


FIGURE 2. Structure of multilayer perceptron (MLP) [28].

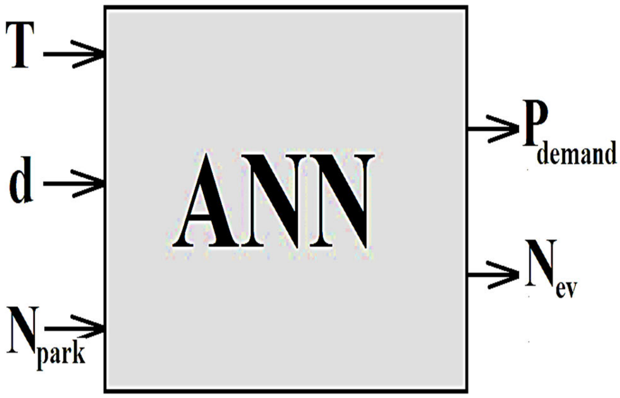


FIGURE 3. The structure is intended to predict the overall demand and the number of electric cars in the parking lot every hour.

network. The parking operator may engage in the day-ahead energy market more profitably by utilizing the information that the neural network produces.

III. PROBLEM FORMULATION

In this section, the problem of optimal planning of bright parking lots is mathematically formulated. The objective function and constraints of the problem are explained separately.

A. OBJECTIVE FUNCTION

Based on the explanations provided, the goal is to minimize the costs related to the intelligent parking operator, the price of buying energy-generating carpets the next day in the market, the cost of buying and selling energy in the balanced market, and the bonus paid to electric car owners. According to the explanations provided, the objective function of the problem is considered as equation 11, which includes the costs of meeting the charging demand of electric vehicles and should be minimized.

$$\mathrm{Min}\sum_{\mathrm{T}=1}^{\mathrm{N_T}}\left(\mathrm{C_t^{DA}}+\mathrm{EC_t^{RT}}\right) \tag{11}$$

In equation 11, C_t^{DA} and EC_t^{RT} are the market cost for the following day and the energy balance market cost in hours t, respectively. The cost related to the reward paid to EV owners is also considered within the equilibrium market cost because this cost is determined when the operator decides to participate in the equilibrium market. The market price for the next day is obtained according to equation 12.

$$C_t^{DA}=\rho_t^{DA,Buy}P_t^{DA,Buy}-\rho_t^{DA,Sell}P_t^{DA,Sell} \tag{12}$$

In this equation, $P_t^{DA,Buy}$ and $P_t^{DA,Sell}$ are the amount of energy bought and sold in the equilibrium market. The parking lot operator can decide to sell energy at certain hours of the day by relying on the ability to discharge the cars in the parking lot to maximize his profit. Also, $\rho_t^{DA,Buy}$ and $\rho_t^{DA,Sell}$ are energy buying and selling prices in the next-day market, respectively. The cost of participating in the real-time market is also calculated as 13.

$$\begin{aligned}EC_t^{RT}&=\sum_{s=1}^{Ns}\pi_s\left(\rho_{t,s}^{RT,Buy}P_{t,s}^{RT,Buy}\right)-\sum_{s=1}^{Ns}\pi_s\left(\rho_{t,s}^{RT,Sell}P_{t,s}^{RT,Sell}\right)\\&\quad-\sum_{s=1}^{Ns}\pi_s\left[\sum_{i=1}^{Nev}\left(\rho_t^{p,ch}P_{i,t,s}^{Ch}-\rho_t^{p,dch}P_{i,t,s}^{Dch}\right)\right]\end{aligned} \tag{13}$$

In this equation, $P_{t,s}^{RT,Buy}$ and $P_{t,s}^{RT,Sell}$ respectively determine the power bought and sold to the network by smart parking for hour t and in scenario s. $\rho_{t,s}^{RT,Buy}$ Moreover, $\rho_{t,s}^{RT,Sell}$ is the price of buying and selling energy in the equilibrium market for hour t and scenario s. π_s The probability of scenario s and Ns is the total number of scenarios. $P_{i,t,s}^{Ch}$ Furthermore, $P_{i,t,s}^{Dch}$ are the charging and discharging power of vehicle i at time t and scenario s, respectively. $\rho_t^{p,ch}$ Moreover, $\rho_t^{p,dch}$ is the agreed price between the parking operator and the owners of electric cars for charging and discharging from the car batteries based on \$/kWh.

As explained, the goal of the electric vehicle operator is to meet the demand for electric vehicle charging at the lowest cost by participating in the day-ahead market and the balance market and with optimal planning in these two markets. Participating in both markets is subject to certain limitations that must be considered and respected by the parking operator. These restrictions are explained for each market separately.

IV. NEXT DAY MARKET RESTRICTIONS

The intelligent parking lot operator's primary responsibility is to provide all the energy required to charge any electric cars that arrive in the lot. Consequently, the energy purchased and sold in the next day's market ought to be sufficient to meet the neural network's estimated total charging need for intelligent parking. Equation 14 is the formulation for this condition.

$$P_t^{DA,Buy}-P_t^{DA,Sell}=P_t^{demand} \tag{14}$$

In this equation, P_t^{demand} is the demand predicted by the neural network for smart parking at hour t. Based on the amount of power bought and sold in the market the next day, the amount of power exchanged in this market is obtained in the form of the following relationship.

$$P_t^{DA} = P_t^{DA,Buy} - P_t^{DA,Sell} \tag{15}$$

In this equation, P_t^{DA} is the amount of power exchanged in the next day's market. According to the prediction made by the neural network for the cars that are present in the parking lot every hour, and relying on the ability to discharge electric cars according to the previous bilateral agreement with the car owners, the parking operator can start selling energy at certain hours in the next day market. Slow: The amount of capacity available in the parking lot should determine how much is scheduled to be sold in the market the next day. The neural network's estimate of the number of automobiles in the parking lot may also be used to determine the lot's capacity. Based on this, equation 16 sets a maximum restriction on the quantity of electricity that may be sold in the market the next day for each hour of parking.

$$P_t^{DA,Sell} \leq Nev_t Cap_{ev} \tag{16}$$

In this equation, Nevt is the number of electric cars in the parking lot at hour t, which the neural network predicts. Capev is the maximum capacity of the car battery that the parking operator is allowed to discharge. In each hour, the parking lot can only sell or buy energy from the grid, and both tasks cannot be done simultaneously. This adverb is also modelled as equations 17 and 18.

$$0 \leq P_t^{DA,Buy} \leq P_{max}^{DA,Buy_t} \tag{17}$$

$$0 \leq P_t^{DA,Sell} \leq P_{max}^{DA,Sell_t} \tag{18}$$

In this equation, zt is a binary variable, if it is one, it indicates the purchase of energy from the grid at hour t, and if it is zero, it indicates the sale of energy to the grid at hour t. Applying clauses 17 and 18, the maximum power bought and sold in the next-day market is also limited. In this equation, $P_{max}^{DA,Buy}$ and $P_{max}^{DA,Sell}$ are the maximum power that can be bought and sold from the parking lot to the network.

A. REAL TIME CONSTRAINTS

Considering that participation in the next-day market is based on the forecast, it is necessary to compensate for the possible changes related to the forecast error. Part of the prediction error compensation for the desired parking lot is done by participating in the real-time market. The decision to charge and discharge electric vehicles is also made simultaneously with the real-time market. As previously said, meeting the demand for car charging is the parking operator's primary responsibility. This is accomplished by taking part in the day-ahead, balancing markets, and draining the cars' batteries while parked in the lot. As a result, the difference between the total charging and discharging power of every car in the parking lot must be equal to the total power exchanged in the day-ahead and balancing markets. Equation 19 is used to formulate this requirement.

$$P_t^{DA,Buy} + P_{t,s}^{RT,Buy} - P_t^{DA,Sell} - P_{t,s}^{RT,Sell}$$
$$= \sum_{i=1}^{Nev} \left(P_{i,t,s}^{Ch} - P_{i,t,s}^{Dch} \right) \tag{19}$$

Based on the power bought and sold in the real-time market, the power exchange in the next-day market is obtained according to the following equation.

$$P_{t,s}^{RT} = P_{t,s}^{RT,Buy} - P_{t,s}^{RT,Sell} \tag{20}$$

The maximum amount of power the parking lot operator is allowed to buy or sell energy to the network is also limited. These constraints are modelled as equations 21 and 22.

$$0 \leq P_{t,s}^{RT,Buy} \leq P_{max}^{RT,Buy_{t,s}} \tag{21}$$

$$0 \leq P_{t,s}^{RT,Sell} \leq P_{max}^{RT,Sell_{t,s}} \tag{22}$$

In this equation, $P_{max}^{RT,Buy}$ and $P_{max}^{RT,Sell}$ are the maximum power that can be bought and sold to the network in the real-time market. In this regard, $y_{t,s}$ is also a binary variable that prevents the simultaneous buying and selling of energy in the equilibrium market.

Electric cars' charging and discharging also face limitations, such as the power of charging and discharging of electric cars is limited. Also, charging and discharging cars simultaneously is impossible, and these restrictions are applied based on equations 23 and 24.

$$0 \leq P_{i,t,s}^{Ch} \leq P_{max}^{Ch_{i,t,s}} \tag{23}$$

$$0 \leq P_{i,t,s}^{Dch} \leq P_i^{Dch,max_{i,t,s}} \tag{24}$$

In these equations, $P_i^{Ch,max}$ and $P_i^{Dch,max}$ are the maximum charging and discharging power of vehicle i, respectively. $u_{i,t,s}$ is a binary variable; if it is one, it indicates the charge, and if it is zero, it indicates the discharge of vehicle I at time t and scenario s. The charge level of the electric vehicle battery in each hour is obtained based on the charge level in the previous hour, the charging power, and the discharging power in the current hour, according to equation 25.

$$SOC_{i,t,s}^{EV} = SOC_{i,t-1,s}^{EV} + \frac{\eta_i^{EV} P_{i,t-1,s}^{Ch,EV} \Delta t}{Cap_i^{EV}} - \frac{P_{i,t-1,s}^{Dch,EV} \Delta t}{\eta_i^{EV} Cap_i^{EV}} \tag{25}$$

In this equation, $SOC_{i,t,s}^{EV}$ is the charge level of the car's battery at time t and scenario s. η_i^{EV} is the charging and discharging efficiency of vehicle i and Δt is the simulation time step. Cap_i^{EV} is also the battery capacity of electric vehicles, i.

The maximum charging and discharging power of electric vehicles is considered fixed. This is while cars' maximum charging and discharging capacity depends on their charging level. For charging levels lower than a specific value indicated by $SOC_i^{Sat\_EV}$, the charging and discharging of vehicles can be considered constant current (CC), equal to the same nominal charging and discharging current. However, for a charge level greater than $SOC_i^{Sat\_EV}$, the charge current is reduced based on the charge level, and the charge correction is performed using the constant voltage (CV) method. In the

CV method, the charging current decreases linearly with increasing SOC. This limitation related to car charging is modelled as equations 26 and 27.

$$0 \le P_{i,t,s}^{Ch} \le P_{max}^{Ch\left(\frac{1-SOC_{i,t,s}^{EV}}{1-SOC_i^{SatEV}}\right)_{i,t,s}} \tag{26}$$

$$0 \le P_{i,t,s}^{Dch} \le P_{max}^{Dch\left(\frac{1-SOC_{i,t,s}^{EV}}{1-SOC_i^{SatEV}}\right)_{i,t,s}} \tag{27}$$

According to the bilateral agreement between the competent parking operator and the owners of electric cars, the charging level of the cars when leaving the parking lot must be greater than a certain level. This condition is also formulated as equation 28.

$$SOC_{i,t_i^{dep},s}^{EV} \ge SOC_i^{depEV} \tag{28}$$

In this equation, $SOC_i^{dep\_EV}$ is the charge level of car I when leaving the parking lot. It is assumed that the value $SOC_i^{dep\_EV}$ has already been communicated to the intelligent parking operator through the electric car owners.

Finally, when electric cars are in the parking lot, their charge level must be maintained between the minimum and maximum allowed values. This stipulation means that the parking lot operator is not allowed to discharge more than the limit of the car battery and prevents excessive depreciation of the car battery. The limitation above is modelled as equation 29.

$$SOC_i^{min\_EV} \le SOC_{i,t,s}^{EV} \le SOC_{i-}^{\max\_EV} t_i^{arr} \le t \le t_i^{dep} \tag{29}$$

In this equation, $SOC_i^{min\_EV}$ and $SOC_i^{max\_EV}$ are, respectively, the minimum and maximum allowed values for the charge level of cars.

V. PROBLEM SOLVING METHOD

All the equations presented for the problem in question are linear except equations 26 and 27. On the other hand, the problem has continuous and binary variables. Therefore, by linearizing two equations, 26 and 27, the desired problem is formulated as a mixed integer linear programming (MILP). In these equations, the term that makes these equations nonlinear is the multiplication of the variable $SOC_{i,t,s}^{EV}$ in the binary variable $u_{i,t,s}$. The multiplication of a binary variable in a continuous variable can be easily linearized. For this, a replacement variable named $\chi_{i,t,s}^{EV}$ is considered. The following restrictions apply for the variable $\chi_{i,t,s}^{EV}$ to be equal to the product $u_{i,t,s}SOC_{i,t,s}^{EV}$.

$$\begin{aligned} \chi_{i,t,s}^{EV} &\le u_{i,t,s} \\ \chi_{i,t,s}^{EV} &\ge 0 \end{aligned} \tag{30}$$

$$\begin{aligned} \chi_{i,t,s}^{EV} - SOC_{i,t,s}^{EV} &\le (1 - u_{i,t,s}) \\ \chi_{i,t,s}^{EV} - SOC_{i,t,s}^{EV} &\ge -\left(1 - u_{i,t,s}\right) \end{aligned} \tag{31}$$

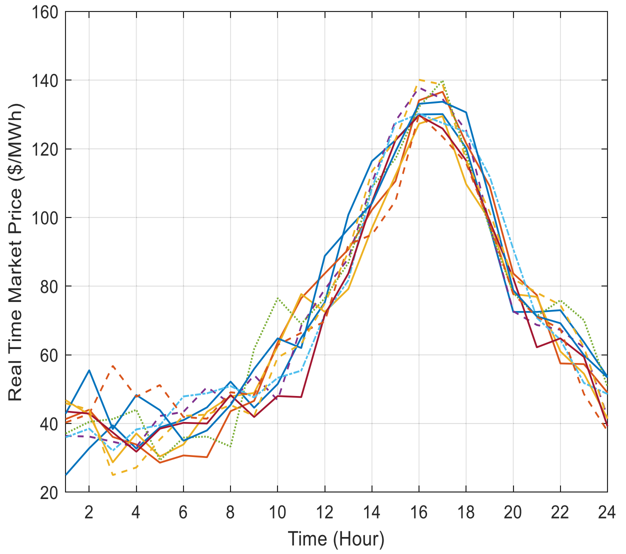


FIGURE 4. Considered scenarios for energy prices in the real time market [29].

VI. SIMULATION RESULTS

In this section, an intelligent parking lot with the capacity to connect 100 electric cars at the same time is considered. As mentioned in the previous sections, the balanced market is associated with uncertainty, and its prices are uncertain until the time of operation. Therefore, the ten scenarios in Figure 4 are considered hourly energy prices for the real-time market [29]. The tariff for selling electricity to electric cars, which the parking operator announces, and the market price of the next day are considered in Figure 5. It is known that the cost of charging electric cars is in the form of a three-time tariff and is based on the time of use (TOU) price.

As explained, the battery capacity of cars is also obtained probabilistically. For this purpose, the probability distribution of battery capacity was used in [27], shown in Figure 6.

The curves depicted in Figure 7 are Gaussian curves that were derived in [30]. These curves were utilized to construct scenarios pertaining to the time of entering the parking lot, the time of leaving the parking lot, and the starting charge level of the charging stations.

According to Figure 7, cars' minimum and maximum charging levels when entering the parking lot are considered 30 and 90 per cent, respectively. The minimum and maximum time to join the parking lot is 5 and 5, and the minimum and maximum time to leave the parking lot is 11 and 24, respectively.

A. NEURAL NETWORK TRAINING

To train the neural network, data collected from actual parking lots, including the time of entry and exit of cars to the parking lot, the battery capacity of electric vehicles, and the charging level of the cars at the time of entering the parking lot, are needed. To train the neural network in this work, data from four different parking lots with capacities of 25, 50, 100, and 200 cars were used during one year. A three-layer

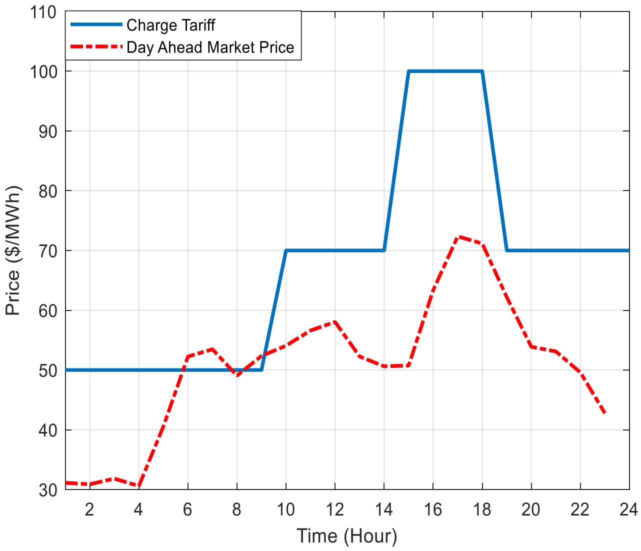


FIGURE 5. Tariff for selling energy to cars and the next day market price [29].

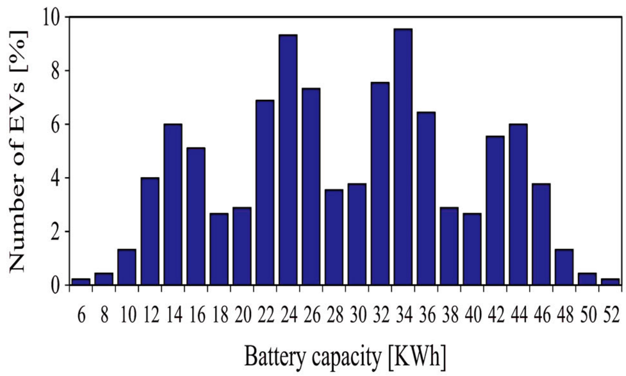


FIGURE 6. Probability distribution of electric vehicle battery capacity [27].

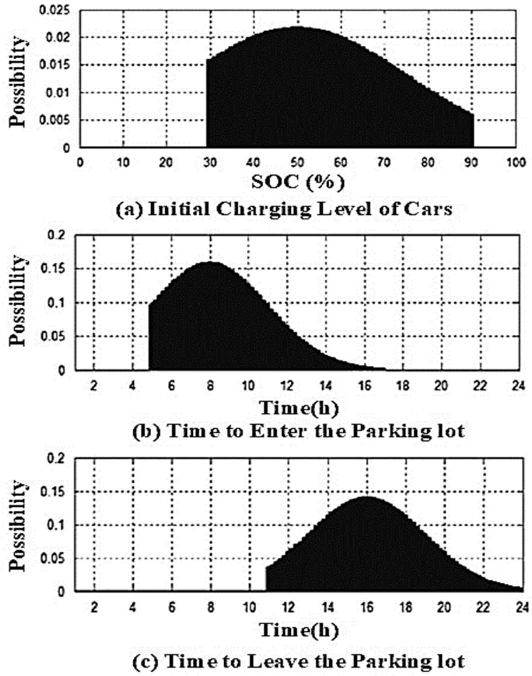


FIGURE 7. Truncated Gaussian distribution parameters related to the characteristics of electric vehicles [30].

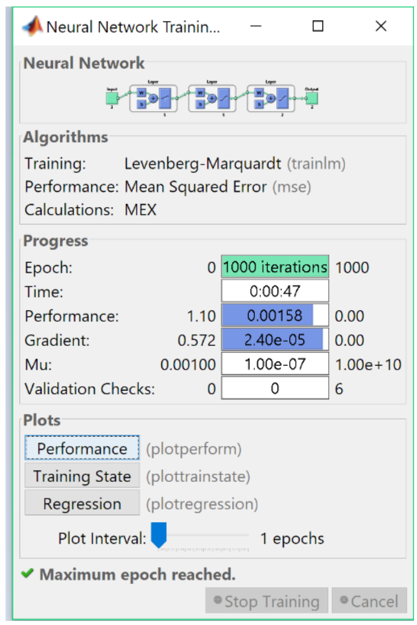


FIGURE 8. Results related to neural network training.

neural network with five hidden neurons in the hidden layer is considered to predict parking behaviour. Figure 8 shows the results of the trained neural network. According to this figure, it is clear that the accuracy of the neural network has reached 0.00158, which is an acceptable value. For a parking lot that can accommodate 100 electric automobiles, Figure 9 displays the charging demand as anticipated by the neural network and its actual value. This method is robustness metric that is attack-independent and can be applied to any arbitrary neural network [31].

Figure 9 shows that the neural network's accuracy is very suitable for estimating the charging demand of cars. Figure 10 also shows the neural network results and accurate information for the number of vehicles in the parking lot for three consecutive days. Based on this figure, it is clear that the neural network has a very high accuracy in estimating the parking behavior of electric cars.

As previously said, the operator decides on the market for the next day based on the output results from the neural network, which include the total charge demand of the parking lot and the number of automobiles there annually.

B. OPTIMIZATION RESULTS

Figure 11 provides the created scenarios for the number of automobiles in the parking lot for each hour of the day, which are used for the modeling of electric cars. Also, the probability distribution of car capacity has been obtained according to Figure 12. In the following, three different cases are considered, and the problem of parking charge management is solved based on the generated scenarios.

To evaluate the proposed model, the following three items are considered:

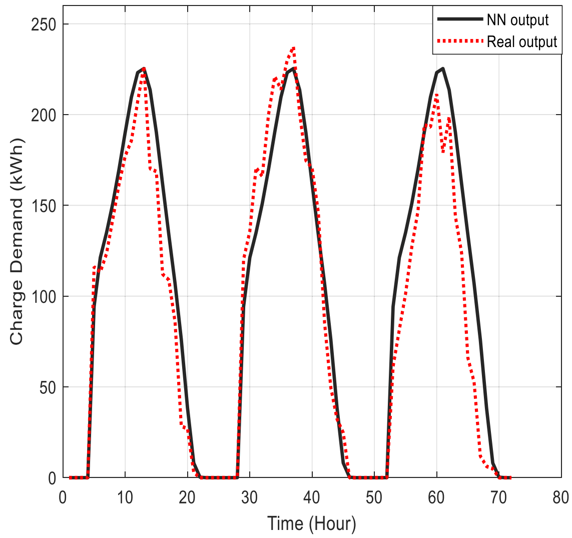


FIGURE 9. Charging demand predicted by the neural network and its actual value for a parking lot with a capacity of 100 electric cars for three consecutive days.

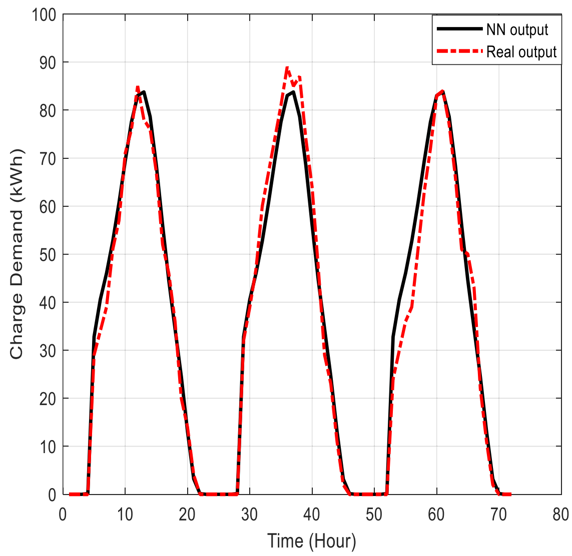


FIGURE 10. Neural network results and real data for the number of cars in the parking lot for three consecutive days.

- Smart parking should meet the entire demand for car charging through participation in the real-time market. In this scenario, it is assumed that the parking operator has no information about the behaviour of the vehicles for the next day, and inevitably, all the charging demand of the vehicles must be met through participation in the balancing market. Also, in this scenario, it is assumed that it is not possible to discharge electric vehicles.
- Smart parking meets the demand for car charging through participation in the next-day and real-time markets. In this scenario, the parking operator, using the neural network, can predict the parking conditions on the next day. Through optimal participation in the day-ahead market and the equilibrium market, he provides the charging demand of the cars. In this scenario, it is also

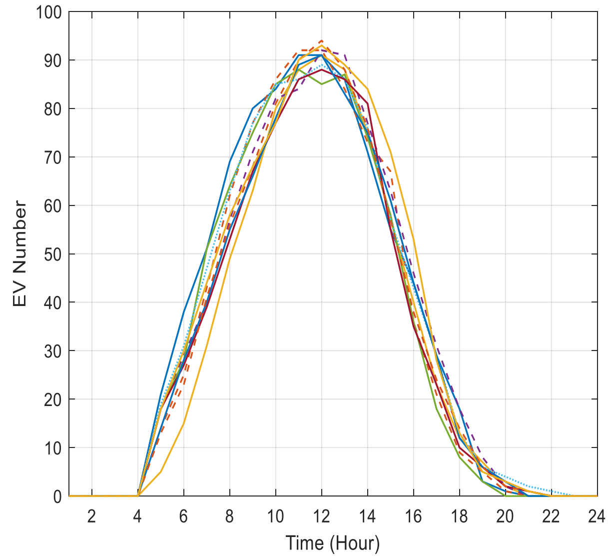


FIGURE 11. Generated scenarios for the number of cars in the parking lot for each hour.

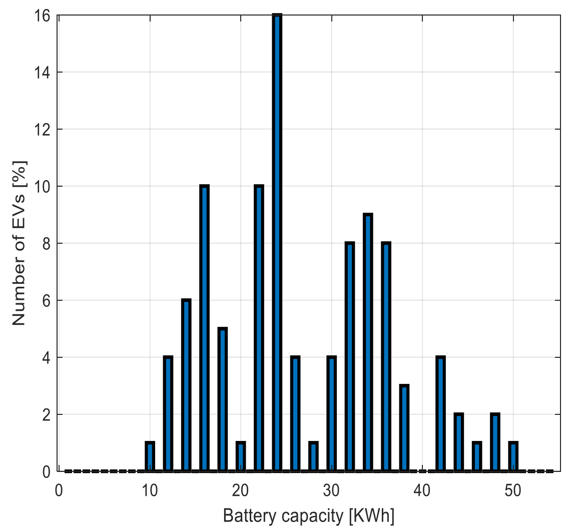


FIGURE 12. Probability distribution obtained for the capacity of cars.

assumed that it is not possible to discharge electric vehicles.
- With the exception of the fact that the parking lot manager is permitted to empty the electric cars' batteries there, it is comparable to item 2.

Based on the three cases defined above, it is possible to evaluate and compare the impact of each of the options for meeting the parking charge demand, i.e., presence in the next-day market, presence in the real-time market, and the possibility of discharging electric vehicle batteries. The results related to each of the mentioned cases are presented and analyzed.

1) RESULTS OF SCENARIO 1

In this case, parking costs only \$8 per day, which is a very little profit. Given that there is no way to discharge the cars in this situation and that the whole amount of power needed to charge them must come from the real-time market, the

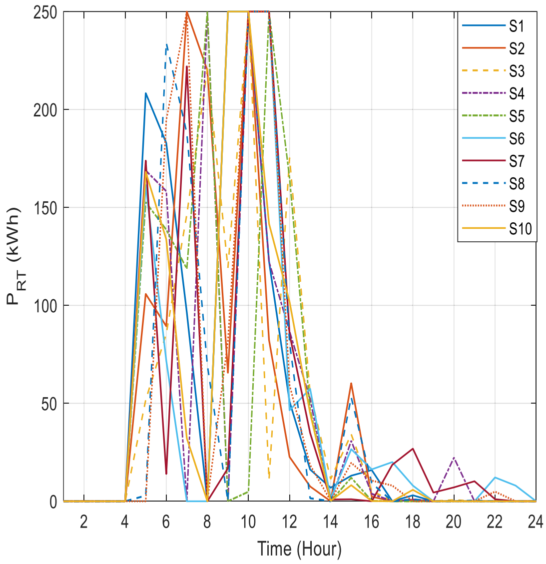


FIGURE 13. The amount of energy exchange of smart parking in the real time market in scenario 1.

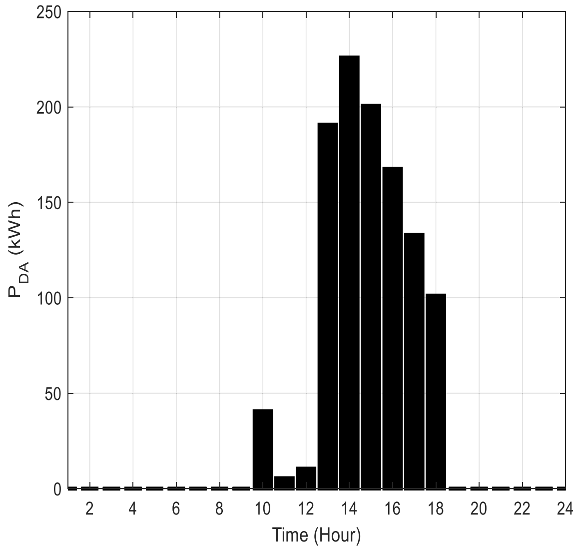


FIGURE 14. The amount of energy purchased from the market the next day in scenario 2.

parking operator has to purchase energy from the network around-the-clock. The energy bought in each scenario from the real-time market is displayed in Figure 12. This energy is equivalent to the energy needed in all circumstances and every hour to charge the automobiles in the parking lot. The energy exchange value of intelligent parking in scenario 1's real-time market is displayed in Figure 13.

Figure 13 makes it evident that, in case 1, there are significant fluctuations in the quantity of energy bought from the real-time market. These fluctuations are brought on by the unpredictability of car behavior, including when cars enter and exit parking lots and the degree of initial charging of electric vehicles. However, there are no alternative possibilities (vehicle unloading or the next-day market), and the real-time market reflects all the uncertainties. It is clear from scenario 1's \$8 profit that parking will not benefit significantly from this kind of power exchange in the real-time market. In this case, the cost of buying energy in the real-time market is \$62.34, and the income from selling energy to electric cars is \$70.38.

2) RESULTS OF SCENARIO 2

In this case, the parking profit equals 32.57 dollars, which has increased by 24.57 dollars compared to the previous situation, equivalent to a triple increase in the intelligent parking profit. This profit increase is due to the participation of smart parking in the next-day market. For this case, the amount of power purchased from the day-ahead market and the real-time market are shown in Figures 14 and 15, respectively. According to Figure 14, most of the energy needed for parking is purchased from the market the next day between 13:00 and 18:00, which is the reason for the high real-time market price during these hours.

A comparison of figures 14 and 15 shows that participation in the day-ahead market has caused a significant reduction in the purchase of energy from the real-time market. Most purchases from the real-time market are related to 10 o'clock, which is the time of transition from low load to medium load. In other words, the parking operator always seeks to supply charging demand prediction errors in the best possible time from the real-time market. At 10 o'clock, when the purchase from the real-time market was high, on the one hand, the price did not increase suddenly, and on the other hand, there were a large number of cars in the parking lot, and the operator was able to charge them. In this instance, the price of electricity purchased from the real-time market is \$3,364, the price of energy purchased from the next-day market is \$62,145, and the revenue from selling energy to automobiles is \$98,085. Due to more automobiles being charged during peak hours, which raised the parking profit, there was an increase in income from the selling of energy to cars as compared to scenario one.

3) RESULTS OF SCENARIO 3

In this case, the cost of removing energy from an electric car's battery is calculated to be 7 cents per kilowatt-hour, or the cost of selling energy to automobiles for an hour of intermediate load. The benefit from smart parking in this instance is \$97.34, which is significantly more than in scenarios 1 and 2. The energy traded in the third scenario's day-ahead market and real-time market are depicted in Figures 16 and 17, respectively.

In Figures 16 and 17, the negative values indicate the sale of energy by parking to the grid. Based on the results, it can be seen that the operator only bought energy in the market the next day and did not sell energy. The reason for this issue is the high uncertainty in the behaviour of cars, which makes it difficult to compensate in the equilibrium market. However, in the real-time market, buying and selling have increased so much that in the early hours of the day, when the real-time

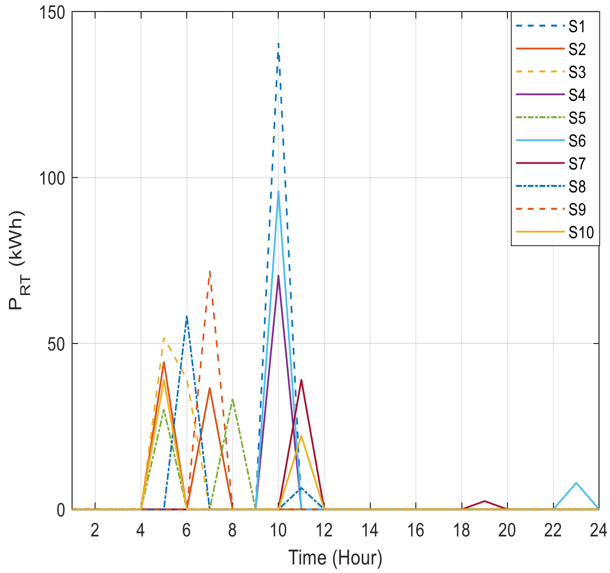


FIGURE 15. Amount of energy purchased from the real time market in scenario 2.

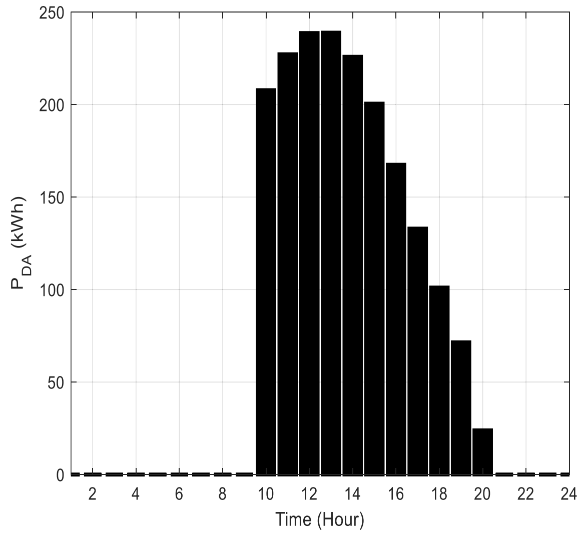


FIGURE 16. Amount of energy exchanged in the next day market in scenario 3.

market price was low, the parking operator bought energy with the maximum capacity and stored it in the car's battery. In addition, with the increase in the real-time market price, the parking operator has sold surplus energy. This is why parking in this case is nearly four times the profit of parking in the second case.

Figures 18 and 19 show the total charging and discharging energy of all cars in each scenario, respectively. Based on these figures, it is clear that most cars were charged in the hours before noon when the real-time market price was low. Most vehicles are discharged at noon and later due to the high real-time market price during these hours. Also, the comparison of Figure 16 with Figure 17 shows that the total amount of car discharge in some hours was more than the energy sold by the parking lot to the grid, which indicates that the parking operator used the car discharge energy to charge other cars.

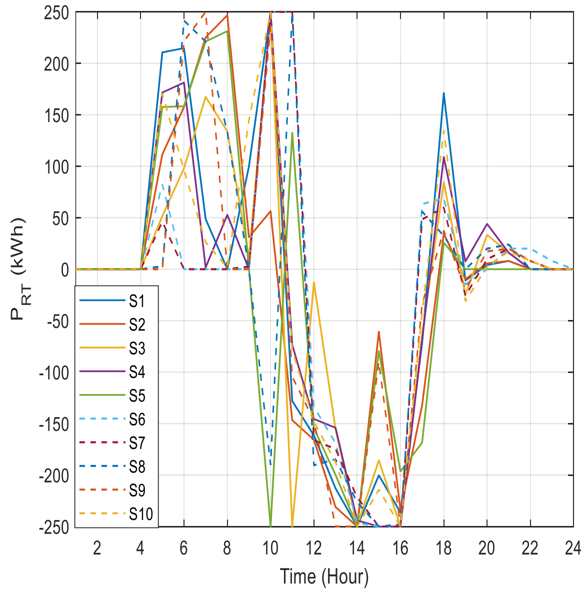


FIGURE 17. Amount of energy exchanged in the real time market in scenario 3.

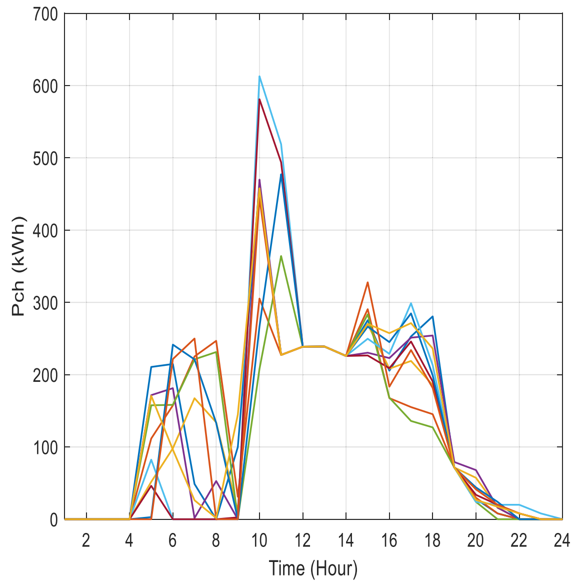


FIGURE 18. Charging energy of all cars per hour for each scenario in scenario 3.

In this case, the difference between the income from the sale of energy to cars and the interest paid to them equals 123 dollars. The cost of the day-ahead market and the real-time market are 46.54 and 105.25 dollars, respectively. The income from the sale of energy in the real-time market equals 126 dollars. Some of the energy purchased in the next-day market has been sold in the real-time market, which has been in line with the increase in profit due to the price difference between these two markets. The results showed that parking participation in different markets and the ability to discharge cars cause a significant increase in the profit of

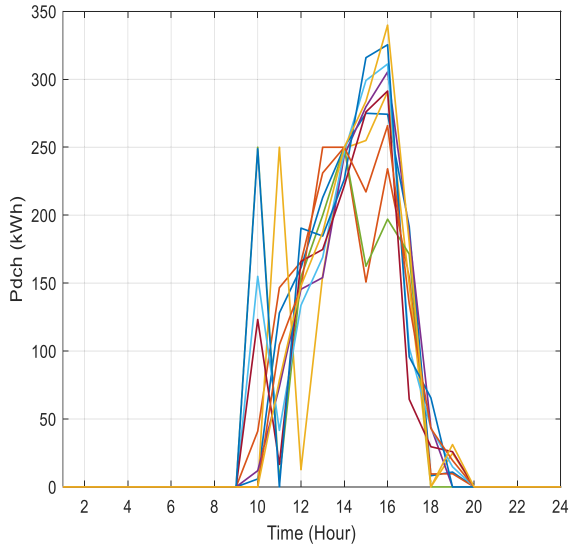


FIGURE 19. Discharge energy of all cars per hour for each scenario in scenario 3.

TABLE 2. Comparison of the results obtained in three study scenarios.

Scenarios	Next Day Market Cost	Real Time Market Cost	Real Time Market Income	Income from Charging	Profit
1	-	62.34	-	70.38	8
2	62.145	3.364	-	98.085	24.57
3	105.25	46.54	126.1	123	97.34

intelligent parking. In Table 2, the results of the three studied cases are compared.

VII. CONCLUSION AND FUTURE WORK

An extensive model for making better use of light parking lots is presented in this research. In this model, an artificial neural network is trained to forecast the total demand for parking fees and the number of automobiles in the parking lot every hour of the next day to participate more profitably in the next-day market. Concurrently with the issue of planning parking participation in the day-ahead market, the real-time market and intelligent car charging/discharging have been developed. The suggested architecture offers the capacity to use a neural network to estimate parking lot charging demand, participate in the day-ahead and balancing markets, and use the ability to discharge electric vehicles for the parking lot operator.

In the coming years, with the increase in the number of electric cars, the number of parking lots will also increase. In such a situation, parking lots must consider electric car owners' benefits in their plans. Providing profit to the owners of electric cars will encourage them to use the desired parking lot again. Therefore, in continuation of this work and to make the proposed model more comprehensive, the problem can be modelled and solved by combining the profit of parking and electric car owners. This work can eventually lead to more use of intelligent parking lots and ultimately increase their profits.

REFERENCES

[1] G. Mittal, A. Garg, and K. Pareek, "A review of the technologies, challenges and policies implications of electric vehicles and their future development in India," *Energy Storage*, vol. 6, no. 1, p. e562, Feb. 2024.

[2] A. Mohammed, O. Saif, M. Abo-Adma, A. Fahmy, and R. Elazab, "Strategies and sustainability in fast charging station deployment for electric vehicles," *Sci. Rep.*, vol. 14, no. 1, p. 283, Jan. 2024.

[3] S. S. A. Naqvi, H. Jamil, N. Iqbal, S. Khan, M. A. Khan, F. Qayyum, and D.-H. Kim, "Evolving electric mobility energy efficiency: In-depth analysis of integrated electronic control unit development in electric vehicles," *IEEE Access*, vol. 12, pp. 15957–15983, 2024.

[4] M. Shirkhani, J. Tavoosi, S. Danyali, A. K. Sarvenoee, A. Abdali, A. Mohammadzadeh, and C. Zhang, "A review on microgrid decentralized energy/voltage control structures and methods," *Energy Rep.*, vol. 10, pp. 368–380, Nov. 2023.

[5] X. Li, Z. Wang, L. Zhang, F. Sun, D. Cui, C. Hecht, J. Figgener, and D. U. Sauer, "Electric vehicle behavior modeling and applications in vehicle-grid integration: An overview," *Energy*, vol. 268, Apr. 2023, Art. no. 126647.

[6] G. Kumar and S. Mikkili, "Advancements in EV international standards: Charging, safety and grid integration with challenges and impacts," *Int. J. Green Energy*, vol. 9, pp. 1–27, Mar. 2024.

[7] H. Ren, C. L. Tseng, F. Wen, C. Wang, G. Chen, and X. Li, "Scenario-based optimal real-time charging strategy of electric vehicles with Bayesian long short-term memory networks," *J. Mod. Power Syst. Clean Energy*, Feb. 2024.

[8] M. R. Alam, S. Saha, M. B. Bostami, M. S. Islam, M. S. Aadeeb, and A. K. M. M. Islam, "A survey on IoT driven smart parking management system: Approaches, limitations and future research agenda," *IEEE Access*, vol. 11, pp. 119523–119543, 2023.

[9] X. Xiao, Z. Peng, Y. Lin, Z. Jin, W. Shao, R. Chen, N. Cheng, and G. Mao, "Parking prediction in smart cities: A survey," *IEEE Trans. Intell. Transp. Syst.*, no. 10, pp. 1–25, Jun. 2023.

[10] A. Debnath and B. Dey, "An interactive approach for parking management system," in *Proc. 2nd Int. Conf. Augmented Intell. Sustain. Syst. (ICAISS)*, Aug. 2023, pp. 937–942.

[11] H. Yang, H. Pan, F. Luo, J. Qiu, Y. Deng, M. Lai, and Z. Y. Dong, "Operational planning of electric vehicles for balancing wind power and load fluctuations in a microgrid," *IEEE Trans. Sustain. Energy*, vol. 8, no. 2, pp. 592–604, Apr. 2017.

[12] E. Mortaz and J. Valenzuela, "Microgrid energy scheduling using storage from electric vehicles," *Electr. Power Syst. Res.*, vol. 143, pp. 554–562, Feb. 2017.

[13] R. Rana, M. Singh, and S. Mishra, "Design of modified droop controller for frequency support in microgrid using fleet of electric vehicles," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3627–3636, Sep. 2017.

[14] P. Aliasghari, B. Mohammadi-Ivatloo, M. Alipour, M. Abapour, and K. Zare, "Optimal scheduling of plug-in electric vehicles and renewable micro-grid in energy and reserve markets considering demand response program," *J. Cleaner Prod.*, vol. 186, pp. 293–303, Jun. 2018.

[15] Y. Yang, Q.-S. Jia, G. Deconinck, X. Guan, Z. Qiu, and Z. Hu, "Distributed coordination of EV charging with renewable energy in a microgrid of buildings," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6253–6264, Nov. 2018.

[16] A. G. Anastasiadis, S. Konstantinopoulos, G. P. Kondylis, and G. A. Vokas, "Electric vehicle charging in stochastic smart microgrid operation with fuel cell and RES units," *Int. J. Hydrogen Energy*, vol. 42, no. 12, pp. 8242–8254, Mar. 2017.

[17] P. R. Da Costa Mendes, J. E. Normey-Rico, and C. B. Alba, "Economic energy management of a microgrid including electric vehicles," in *Proc. IEEE PES Innov. Smart Grid Technol. Latin Amer. (ISGT LATAM)*, Oct. 2015, pp. 869–874.

[18] M. Zhang and J. Chen, "The energy management and optimized operation of electric vehicles based on microgrid," *IEEE Trans. Power Del.*, vol. 29, no. 3, pp. 1427–1435, Jun. 2014.

[19] A. El-Zonkoly, "Intelligent energy management of optimally located renewable energy systems incorporating PHEV," *Energy Conver. Manag.*, vol. 84, pp. 427–435, Aug. 2014.

[20] E. R. Ghadikolaei, A. Ghafouri, and M. Sedighi, ‘‘Probabilistic energy management of DGs and electric vehicle parking lots in a smart grid considering demand response,’’ *Int. J. Energy Res.*, vol. 2024, pp. 1–21, Feb. 2024.

[21] L. Bagherzadeh and I. Kamwa, ‘‘Joint multi-objective allocation of parking lots and DERs in active distribution network considering demand response programs,’’ *Energies*, vol. 16, no. 23, p. 7805, Nov. 2023.

[22] S. Mohseni, R. Khalid, and A. C. Brent, ‘‘Stochastic, resilience-oriented optimal sizing of off-grid microgrids considering EV-charging demand response: An efficiency comparison of state-of-the-art metaheuristics,’’ *Appl. Energy*, vol. 341, Jul. 2023, Art. no. 121007.

[23] H. Hosseinnia, B. Mohammadi-Ivatloo, and M. Mohammadpourfard, ‘‘Optimal techno-economic planning of a smart parking lot—Combined heat, hydrogen, and power (SPL-CHHP)-based microgrid in the active distribution network,’’ *Appl. Sci.*, vol. 11, no. 17, p. 8043, Aug. 2021.

[24] Y. Yu, O. S. Nduka, F. U. Nazir, and B. C. Pal, ‘‘A three-stage stochastic framework for smart electric vehicle charging,’’ *IEEE Access*, vol. 11, pp. 655–666, 2023.

[25] H. M. Mohan and S. K. Dash, ‘‘Renewable energy-based DC microgrid with hybrid energy management system supporting electric vehicle charging system,’’ *Systems*, vol. 11, no. 6, p. 273, May 2023.

[26] R. J. Bessa, M. A. Matos, F. J. Soares, and J. A. P. Lopes, ‘‘Optimized bidding of a EV aggregation agent in the electricity market,’’ *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 443–452, Mar. 2012.

[27] M. Shafie-khah, E. Heydarian-Forushani, G. J. Osório, F. A. S. Gil, J. Aghaei, M. Barani, and J. P. S. Catalão, ‘‘Optimal behavior of electric vehicle parking lots as demand response aggregation agents,’’ *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2654–2665, Nov. 2016.

[28] Y. K. Jemal, ‘‘Plug-in electric vehicle charging impacts on power systems,’’ M.S. thesis, Chalmers Univ. Tech, Goteborg, Sweden, 2010.

[29] A. Gholami, T. Shekari, F. Aminifar, and M. Shahidehpour, ‘‘Microgrid scheduling with uncertainty: The quest for resilience,’’ *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2849–2858, Nov. 2016.

[30] E. Heydarian-Forushani, M. E. H. Golshan, and M. Shafie-khah, ‘‘Flexible interaction of plug-in electric vehicle parking lots for efficient wind integration,’’ *Appl. Energy*, vol. 179, pp. 338–349, Oct. 2016.

[31] T.-W. Weng, H. Zhang, P.-Y. Chen, J. Yi, D. Su, Y. Gao, C.-J. Hsieh, and L. Daniel, ‘‘Evaluating the robustness of neural net-works: An extreme value theory approach,’’ in *Proc. ICLR*, 2018.

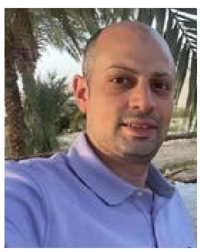
MAJID VALIZADEH received the B.Sc. degree in electrical engineering from Kashan University and the M.Sc. and Ph.D. degrees in electrical engineering from the University of Tabriz, Iran, in 2013. He is currently an Assistant Professor with Ilam University. He has several management experiences in industries. He has been the author and co-author of many journals and conference papers in the fields of power system protection, power electronics, energy management in power systems, and energy optimization.

FARSHAD MORADI received the B.Sc. degree in electrical engineering from Shahid Rajaei University, Kashan, Iran, and the M.Sc. degree in electrical engineering from Ilam University, Ilam, Iran, in 2021. His research interests include energy management of smart parking lots and microgrids.

AMIRHOSSEIN KHOSRAVI SARVENOEE was born in Ahvaz, in 2000. He received the bachelor’s degree in electrical engineering from Ilam University, in 2023, where he is currently pursuing the master’s degree in electrical engineering. His research interests include renewable energy, microgrids, smart grids, and power systems.

MOHAMMAD KOHZADIPOUR received the B.Sc. and M.Sc. degrees in electrical engineering from Ilam University, Ilam, Iran, in 2023. His research interests include energy management of smart parking lots and microgrids.

N. GOWTHAM (Senior Member, IEEE) received the bachelor’s degree in electrical and electronics engineering from the Vidyavardhaka College of Engineering, Mysuru, in 2011, the M.Tech. degree in microelectronics and control systems from the Dayananda Sagar College of Engineering, Bengaluru, in 2013, and the Ph.D. degree in electrical power quality from Visvesvaraya Technological University, Belagavi, in 2020. He was a Research Fellow with IIT Delhi. He was with Bosch Automotive Electronics, Bengaluru. Currently, he is an Associate Professor with the Department of Electrical and Electronics Engineering, Manipal Institute of Technology Bengaluru. He has published books and book chapters. He has authored more than 20 research papers in reputed conferences and journals. His research interests include applications of power electronics to power systems, power quality, integration of RE into LV/MV grids, and engineering education.



KAREEM M. ABORAS received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the Faculty of Engineering, Alexandria University, Alexandria, Egypt, in 2010, 2015, and 2019, respectively. His Ph.D. research work is focused on the performance enhancement of renewable energy conversion systems. Currently, he is an Assistant Professor with the Electrical Power and Machines Department, Faculty of Engineering, Alexandria University. His research interests include power electronics, control, drives, power systems, smart grids, microgrids, power quality, optimizations, electric vehicles, machine learning, modeling, fuel cells, HVDC, and renewable energy systems. He is a Reviewer for IEEE TRANSACTIONS ON ENERGY CONVERSION, *Electric Power Systems Research*, *Smart Science*, *Alexandria Engineering Journal* (IET), *Energy Reports*, IEEE ACCESS, *Cybernetics and Systems*, *Protection and Control of Modern Power Systems* (MDPI), *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *Cogent Engineering*, and Hindawi journals.