University of Birjand

Iranian Journal of Power Engineering (2026) Vol. 2, No. 1:65-71

10.22077/ijpe.2025.9618.1022

ORIGINAL ARTICLE

Smart Energy Management of Electric Vehicle Parking Lots within Dynamic Electricity Market

Homa Rashidizadeh-Kermani [a*], Mahdiar Cheraghi [b], Arsalan Najafi [c], *Senior Member, IEEE*

[a] Research and Innovation Division, Nowocert, Dublin, Ireland
[b] Research and Technical Division, Saha Niroo Savis Company, South Khorasan, Iran
[c] Geology and Geotechnics, Architecture and Civil Engineering, Chalmers University of Technology

[*]Corresponding Author, Email Address: rashidi.h@nowocert.com
Submitted: 19 June 2025, **Accepted:** 13 November 2025, **Published**: 06 November 2026

Abstract

In this paper, the problem of decision making for an electric vehicle parking lot during a short-term time horizon in a competitive environment is modeled as a bi-level problem. Several electric vehicle parking lots compete with each other in a competitive space to supply energy to vehicles. Electricity market prices, the bidding prices of competing parking lots, and the stochastic nature of drivers' behavior transform the decision-making problem into a probabilistic one. Therefore, the proposed problem is formulated probabilistically and in two levels. In the first level, the electric vehicle parking lot seeks to maximize its profit by participating in the short-term power pool market, including day-ahead and balancing markets. The second level there are electric vehicle owners who try to supply their required energy from the cheapest aggregator. The results show the impact of risk averse behavior of aggregators on the energy purchased from the network in day ahead and balancing markets.

Keywords: Renewable energies, bi-level problem, day-ahead scheduling, demand response, electric vehicle.

Nomenclature

Indices

$\perp$	The sign to show the production of two vectors is zero.
Ch(dch)	Process of charge (discharge).
DA	Day-ahead market.
Pos (neg)	Positive (negative) balancing market.
S	Index of aggregators.
ξ	Index of rival aggregator scenarios.
t	Index of time.
ω	The index of scenarios.
$(\cdot)_{t,\omega}$	At time t and scenario ω.

Variables

$e_s^{X/Z\ ch/dch}(\xi)$	Binary variable for complementary slackness conditions.
$E_{t,\omega}^{ch/dch}$	The supplied energy by the main aggregator (MWh).
$E_{t,\omega}^{pos/neg,B}$	Balancing deviation (MWh).
$K_{ch/dch}^{s,s'}$	Reluctance of EV owners to shift among aggregators (€).
$Re\ v_{t,\omega}^{ch/dch}$	The income/payment of the under study aggregator for charge/discharge process (€).
$X_s^{ch/dch}(\xi)$	Share of main aggregator to supply EVs ξ.
$X_{s0}^{ch/dch}(\xi)$	Percentage of EVs supplied by the main aggregator in scenario ξ.
$Z_{ch/dch}^{S,S\prime}(\xi)$	Shifted EVs between aggregators in scenario ξ.
$C_{t,\omega}^{ch/dch}$	Offering price signal of the aggregator (€/MWh).
$\iota(\omega)$	Auxiliary variable in risk management.
$\varepsilon_s(\xi)$	Lagrange multiplier of the balance of sharing demand.
$\varphi(\xi)$	Lagrange multiplier for balancing power.
$SoC_{t,\omega}$	State of charge of EV.

Parameters

$E_{t,\omega}^{D_{ch/dch}}$	Required demand of EVs (MWh).
$\hat{E}_t^{D_{ch/dch}}$	Total expected EVs demand (MWh).
$P_{t,\omega}^{DA}$	DA energy procurement to supply EVs demand (MWh).
$X_{S_{ch/dch}}^0(\xi)$	Initial demand supplied by each aggregator.
$\pi(\omega)$	Probability of occurrence of scenarios
$\lambda_{t,\omega}^{+/-,B}$	Balancing prices (€/MWh).
$\lambda_{s,t,\xi}^{ch/dch}$	Price signals offered by aggregators (€/MWh).
$\lambda_{s_0,t}^{ch/dch}$	Price signals offered by the under study aggregator (€/MWh).
$\lambda_{t,\omega}^{DA}$	DA price (€/MWh).
$\hat{C}_t^{DA}$	Expected DA price (€/MWh).
$\upsilon(\xi)$	Probability of occurrence of prices

	offered by rival aggregators in scenario ξ.
α	Confidence level for calculation of CVaR.
β	Risk factor.
Δ	Relation between demand and price.
$\eta^{ch/dch}$	Charge/discharge efficiency.
$\underline{SoC}/\overline{SoC}$	*SoC* limitation.
E^{Cap}	EVs capacity (MWh).
$\bar{P}^{ch/dch}$	Limitation of charge/discharge (MWh).
	Sets
T	Number of Time periods
S	Number of aggregators
ω	Number of DA prices, balancing prices and EVs charge/discharge scenarios.
Ξ	Number of rival aggregators' scenarios.

1. Introduction

Obtaining sustainability goals, while keeping or augmenting achieve to energy services requires multi-dimensional replies. Efforts to reach smart and limited energy systems are one of these responses, involving a paradigm shift that moves the energy system from big power plants and reserves resources toward more flexible structure that exploit (Barnes et al. 2024) the generation of renewable energy. These systems include highly distributed physical tools, players, skills, and control systems. Renewable energy sources (RES) have developed highly recently because of their low emissions and operational costs. However, they reduce the system's flexibility due to the intermittency in their generation. Here, flexibility shows to the capability of a system to coordinate with the external prices or activation signals in order to supply services to its consumers through the generation and/or consumption. This index can be developed (Ranjbar et al. 2024) by showing flexible resources into the network. The utilization of the network, as well as issues like feeder losses, voltage drop, and load fluctuations, has been examined in different charging modes based on (Ranjbar et al. 2024; Richardson et al. 2011) time and charging rates of vehicles.

In (Ranjbar et al. 2024), energy management concept is used to develop the efficiency and flexibility of the distribution system with distributed batteries and RES. Injecting high values of RES to a network reduces its flexibility because of predicting RES generation is challenging. Therefore, batteries are added as flexibility sources to augment operational indices and strengthen the flexibility of the distribution network. In (Deilami et al. 2011), a centralized charging strategy was proposed to minimize losses and voltage drop, and in (Yang et al. 2014), an optimal charging and discharging method for electric vehicles was suggested.

Electric vehicles (EVs), through their charging and discharging, must participate in the electricity market and sometimes even compete with other market participants. However, due to market rules that restrict individual EV participation, there is an emphasis on the need for an aggregator institution for EVs (Kempton et al. 2001; Lopes et al. 2010). In (Gkatzikis et al. 2013), the relationship between the network operator, parking lots, and loads, and optimal decision-making by each are discussed.

In recent years, various methods have been used to forecast electricity market prices. In (Contreras et al. 2003), time series methods were applied to market data from Spain and Norway, and in (Ramsay and Wang 1997), artificial neural networks were used with data from UK electricity markets to predict prices. Day-ahead price forecasting using data from California and Spain is modelled in. To price locally, a model was used in (Li, R et al. 2013) for EV parking lots to mitigate congestion caused by EV load. In (Pirouzi and Aghaei 2019), a model for managing active and reactive power at EV parking lots in distribution networks is explained. This study considers the operational cost minimization as a normalized objective function with the optimal power flow in the network with EV parking lots as a limitation. The results show that the energy management strategy corrects the energy loss and voltage profiles. Additionally, the distribution network supplied energy to most of EVs.

In (Harighi et al. 2024), a hybrid model is proposed that shows the flexibility potential of parking lots with different EV charging locations. This model is implemented in a stochastic optimization process to forecast the maximum flexibility limitations of the parking lot. The EV aggregator, responsible for the charging stations, offers intra-day ancillary services to the grid by determining the possible margins within which the energy can vary, either up or down.

In this paper, a decision-making problem for an electric vehicle aggregator in a short-term time horizon within a competitive space is presented in the form of a bi-level problem. It is assumed that a set of electric vehicles, through charging stations in a parking lot equipped with measurement devices and smart charging/discharging equipment, exchange energy with the grid. Additionally, multiple EV aggregators compete with each other to supply power to the vehicles. It is noteworthy that probabilistic data, such as electricity market prices, proposed prices from competing aggregators, and the random nature of vehicle owner behaviour, make the decision-making problem probabilistic. Therefore, the proposed problem is structured in two levels. In the first level, the EV aggregator tends to maximize its profit by taking part in the short-term power pool market. In this step, the amount and timing of energy purchases from the day-ahead market are determined. In the second step, given the output from the first step, as well as scenarios of balancing market prices and vehicle load information, the charging and discharging energy at each moment and the proposed prices to the vehicle owners are calculated.

2. Proposed model

Must propose charging and discharging prices to vehicle owners in a way that incentivizes them to purchase their required charge from the parking lot and sell their surplus stored energy back to it. Additionally, to maximize its profit, the parking lot needs to offer higher prices for charging to vehicle owners and, conversely, purchase the energy discharged from vehicles at a lower price. However, since the target market operates within a competitive environment, the parking lot cannot propose excessively high prices for charging (or excessively low prices for discharging). In such a competitive environment, it risks losing some of its customers.

Therefore, the parking lot must also consider the pricing scenarios proposed by competing parking lots to maintain or even increase its customer base within the competitive space.

At the lower level, the vehicle owner must comply with the technical constraints of the vehicle while minimizing the cost of charging it. Furthermore, during periods when the vehicle is not being used for transportation, the energy stored in its battery should be sold to the grid at a high price.

3. Problem formulation

The objective functions of the upper and lower levels of the proposed problem are in conflict with each other; that is, the profit of one result in higher costs for the other. Therefore, the problem is formulated as a bi-level optimization model. The objective function in this framework is as follows:

$$\underset{\substack{E^{DA}_{t,\omega},E^{+,B}_{t,\omega},E^{-,B}_{t,\omega}\\ \lambda^{ch/dch}_{t,\omega},E^{ch/dch}_{t,\omega},\zeta,t(\omega)}}{Maximize} \sum_{\omega\in\Omega} p(\omega)\sum_{t\in T}\begin{bmatrix} E^{ch/dch}_{t,\omega} - E^{DA}_{t,\omega}\lambda^{DA}_{t,\omega} \\ -E^{+,B}_{t,\omega} + E^{-,B}_{t,\omega}\lambda^{DA}_{t,\omega}\end{bmatrix} \tag{1}$$
$$+\beta\left[\zeta - \frac{1}{1-\alpha}\sum_{\omega\in\Omega} p(\omega)t(\omega)\right]$$

$$E^{ch}_{t,\omega} - E^{dch}_{t,\omega} = E^{DA}_{t,\omega} + E^{+,B}_{t,\omega} - E^{-,B}_{t,\omega} \quad \forall t\in T, \quad \forall\omega\in\Omega \tag{2}$$

$$-\sum_{t\in T}\left[E^{ch/dch}_{t,\omega}\lambda^{ch/dch}_{t,\omega} - E^{DA}_{t,\omega}\lambda^{DA}_{t,\omega} - E^{+,B}_{t,\omega}\lambda^{+,B}_{t,\omega} + E^{-,B}_{t,\omega}\lambda^{-,B}_{t,\omega}\right] \tag{3}$$
$$+\zeta - t(\omega)\le 0, \quad \forall\omega\in\Omega$$

$$t(\omega)\ge 0, \quad \forall\omega\in\Omega \tag{4}$$

$$E^{ch/dch}_{t,\omega} = E^{Dch/dch}_{t,\omega}\sum_{\xi\in[1]} v(\xi)X^{Dch/dch}_{S0}(\xi) \quad \forall t\in T, \quad \forall\omega\in\Omega \tag{5}$$

$$E^{DA}_{t,\omega} = E^{DA}_{t,\omega'} \quad \forall t\in T, \ \forall\omega\in\Omega \tag{6}$$

$$E^{+,B}_{t,\omega} \le P^{\max} \quad \forall t\in T, \quad \forall\omega\in\Omega \tag{7}$$

$$E^{-,B}_{t,\omega} \le E^{ch}_{t,\omega} \quad \forall t\in T, \quad \forall\omega\in\Omega \tag{8}$$

Here, Equation (1) identifies the goal function, which consists of two components: the first part pertains to the profit of the parking lot, and the second part reflects the risk function (CVaR) (Rashidizadeh et al. 2020). In this model, the CVaR function is added to the profit function with a weighting coefficient, α, which indicates the significance of risk in the parking lot's profit function. Equation (2) expresses the energy balance constraint. Equations (3) and (4) are related to risk control. The amount of charging and discharging loads of vehicles by the parking lot is described in Equations (5) and (6). Equation (7) states that the amount of energy purchased in the day-ahead market for similar prices must be identical. The energy

exchanged in the negative balancing market is limited in Constraint (8).

4. Case study and numerical results analysis

To numerically evaluate the proposed bi-level model, a sample system with real-world electricity market data is used. The overall structure of the studied system is shown in Fig.1. As observed, the system includes four parking lots, where parking lot S_0 is the parking lot under study, and parking lots S_1 to S_3 are the competing parking lots. The total number of electric vehicles in this study is considered to be 100, each with a battery capacity of 16 kWh. The parking lot under study must plan for a short-term period of the next 24 hours in a competitive environment with the objective of maximizing its profit. It should be noted that each parking lot has access to historical electricity market data and the total load information of the vehicles.

In this study, the electricity prices for the day-ahead and balancing markets are extracted from the Nord Pool electricity market in 2016. To model uncertainties arising from prices, including day-ahead prices, positive balancing prices, and negative balancing prices, 200 scenarios for each price parameter are generated using the ARIMA time-series model (Gkatzikis et al. 2013). Fig.2 illustrates the generated scenarios for day-ahead prices, positive balancing prices, negative balancing prices, and the load of electric vehicles. After generating scenarios for each uncertain parameter, scenario reduction techniques are implemented to decrease the amount of scenarios for each random parameter to 7, improving the solution time of the problem. Then, using the concept of a scenario tree, the reduced scenarios are combined, resulting in 343 scenarios that are ultimately used in the proposed problem.

Additionally, in this study, the discharging load of vehicles is assumed to be 20% of their charging load. The initial state of charge (SOC) of the vehicles in each scenario is randomly generated while considering the technical constraints. Similarly, the charging and discharging loads of the vehicles by both the studied parking lot and the competing parking lots are randomly generated for each hour. The probabilistic bi-level programming problem is formulated as a Mixed-Integer Linear Programming (MILP) problem and solved using the commercial solver CPLEX in GAMS software (Vahedipour et al. 2020). Simulation results are presented for two cases: with and without considering the CVaR risk measure.

In this study, the amount of energy exchanged with the grid in the day-ahead, positive, and negative balancing markets with a risk coefficient of β=10 is presented in Figures 3-5. As can be seen, during mid-night hours, the people attempt to charge their automobiles and use the stored energy in the battery throughout the day to go to work. Additionally, some car owners recharge their vehicles for use in the evening. As shown in Fig.1, the day-ahead market prices are low during midnight and the early morning hours. Therefore, this is a suitable time for the parking lot to meet the needs of vehicle owners with minimal cost. Since the cars' energy needs are met with energy purchased from the day-ahead market during these hours, the parking lot does not participate much in the positive balancing market to increase its purchase amount. Additionally, during these hours, the parking lot attempts to reduce some of its load and gain profit based on the negative balancing market prices.

Between 8:00 AM and 8:00 PM, when cars are generally used for transportation purposes, their requested load is low. Therefore, the parking lot participates minimally in both markets. At 1:00 PM, the average prices for the day-ahead and positive balancing trading floors are 15.27 €/MWh and 31.29 €/MWh , respectively. Since the day-ahead market price is cheaper than the positive balancing market price at this hour, the parking lot purchases 35.73 kWh from the day-ahead market. Then, to meet the needs of car owners, it purchases 24.45 kWh of energy from the positive balancing market.

At 9:00 PM, the expected price for the positive balancing market is 15.26 €/MWh, while the day-ahead market price is 28.02 €/MWh. Although the positive balancing market prices are totally more than the day-ahead market prices, the opposite occurs at this hour. As a result, the parking lot attempts to purchase more services from the positive

balancing market to pay less. From 10:00 PM to midnight, as there is a significant load connected to the grid, the parking lot strives to meet this load from the day-ahead market (that is cheaper).

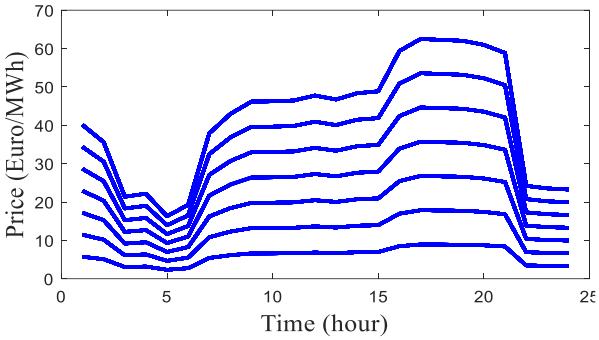


Fig.1. Generated scenarios for day-ahead market prices

It can be observed that whenever vehicles request a significant amount of load from the grid, the parking lot attempts to meet the demand from the cheaper floor. Additionally, by participating in the negative balancing market, it also aims to gain profit. The severe fluctuations observed in the negative balancing prices are intended to encourage the parking lot to reduce its load or discharge.

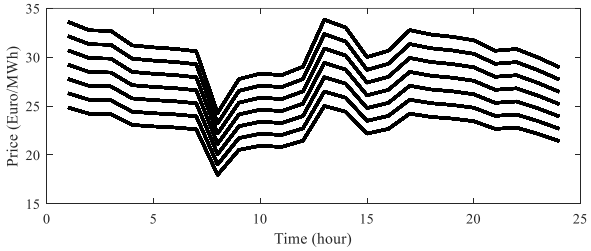


Fig.3. Generated scenarios for positive balancing market prices

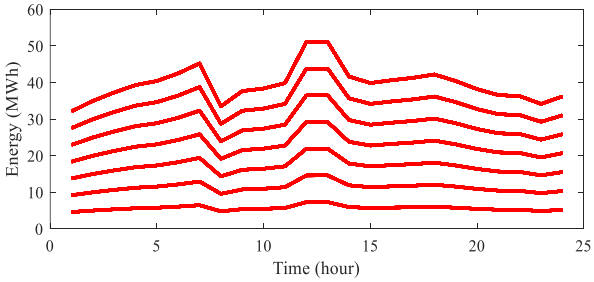


Fig.3. Generated scenarios for negative balancing market prices

In this section, to perform a sensitivity analysis, the effect of the risk mitigation parameter (β) in the problem is examined. In this study, due to the uncertainty of electricity prices in the electricity market, the charging and discharging load of vehicles, and the uncertainty of the proposed charging and discharging prices by competing parking lots, risk analysis is used as a tool to deal with the probabilistic nature of the problem.

For better analysis, the expected value of parking's profit in terms of CVaR is presented in Fig.6. The boundary shown in this figure indicates the characteristics of the parking lot in dealing with the uncertainties in the problem, and consequently, the level of risk tolerance of the parking lot. As observed, with an increase in β, the average profit of the parking lot decreases.

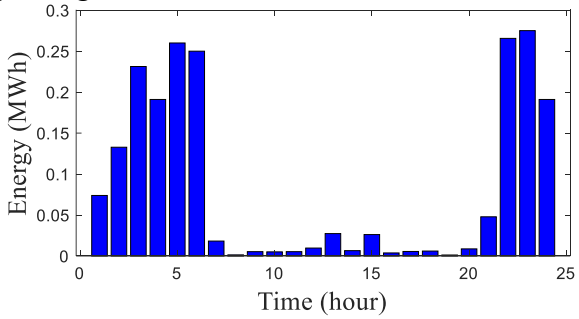


Fig.4. The amount of energy supplied from the day-ahead market

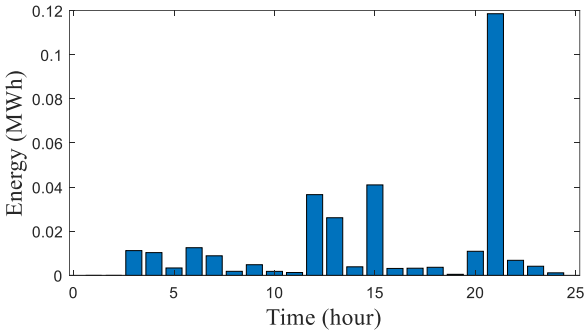


Fig.5. The amount of energy supplied from the Positive Balancing Market

Additionally, after (β = 1), the average profit of the aggregator drops suddenly. This is because when the parking lot tries to mitigate the risk, it prefers to buy from a more reliable market, which in this case is the positive balancing market, which is also more expensive. This causes the profit of the parking lot to decrease. From another perspective, with an increase in the risk mitigation coefficient, profits that deviate from the mean are excluded. For example, some scenarios may yield very high profits for the parking lot, but since the parking lot is risk-averse, it disregards these scenarios. Furthermore, it can be observed that the CVaR is negative.

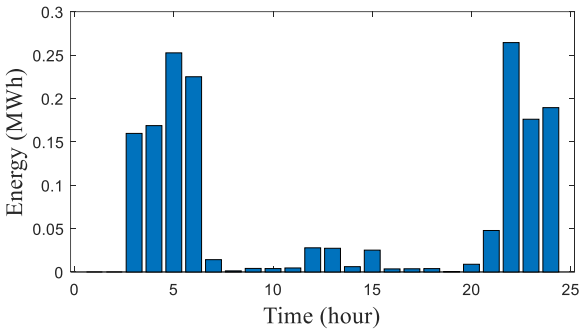


Fig.6. The amount of energy exchanged with the negative balancing market

The reason for this is the presence of some scenarios with negative profit, or in other words, losses for the parking lot. As the risk-aversion factor increases, scenarios that deviate from the average profit are eliminated, including those with negative profits. Consequently, as β increases, the CVaR becomes more positive. In other words, by increasing the risk-aversion coefficient, not only are some scenarios with positive profits that deviate from the average removed, but scenarios with negative profits that deviate from the average are also eliminated. Thus, the profit curve is trimmed from both sides of the average profit, so that with an increase in β, the system always operates around the average profit value

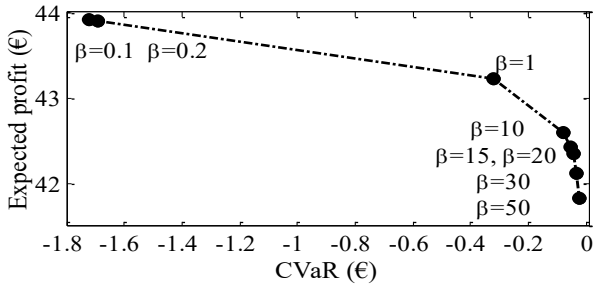


Fig.7. Changes in the Expected Profit in Terms of CVaR Considering the Effect of β.

The probability of profit scenarios at two different β values, 0.1 and 50, at 19:00 is shown in Fig.7. Although at this hour, the profit for the aggregator is minimal at both risk coefficient values, which may not be worth discussing, the profit of the parking lot is examined because both the charge and discharge prices reach their peak values during this time. At 19:00, when β = 0.1, due to the extremely high charge and discharge prices offered to customers, the profit of the parking lot significantly decreases. Moreover, the variability of parking lot's profit at this β value is high, and many of the scenarios result in negative profits. The spread in profit occurs because, at this risk coefficient, the parking lot is risk-averse and offers a high discharge price to customers. The negative profit results because both the charge and discharge prices are high during this hour, causing the parking lot to lose charging customers while having an influx of discharge customers.

At β = 50, since the discharge signal is cheap and the charge signal is expensive at this hour, although in some scenarios, the parking lot earns a profit, it is usually around zero. Additionally, at this risk coefficient, the discharge price decreases, which reduces the number of negative profit scenarios. Also, with the increase in the charge price, although the parking lot makes some profit in certain scenarios, it generally loses its customers and ends up with a minimal profit.

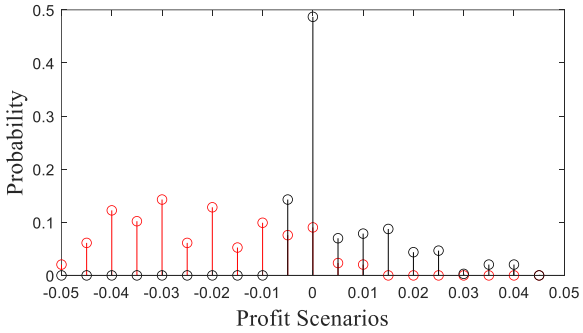


Fig.7. Parking profit in all scenarios at $\beta = 0.1$ and $\beta = 50$ at 19:00.

5. Conclusion

In this paper, due to the uncertainties arising from market prices and the prices proposed by competitors, the CVaR concept was used as a measure to manage the risk of these uncertainties in the planning of charging and discharging electric vehicles in a parking lot. The results showed that as the risk coefficient increases, the parking manager attempts to purchase more from a market that is more stable. Since the balancing market is more stable but has higher prices, the parking lot must pay higher costs in the balancing market, resulting in a lower expected profit. Therefore, the results indicate that with an increase in CVaR, the aggregator must pay more in the balancing market, and consequently, its profit decreases.

6. Acknowledgement

The authors want to thank *Saha Niroo Savis Company* for their financial support to this work that is related to the project (SGRI-

PRO/0001/2025) for "Integration of Photovoltaic Systems to the rural places in South Khorasan".

7. Reference

Barnes, J., Darby, S., & Hansen, P. (2024). Smartening Local Energy in Europe: A Comparative Analysis of Three Cases and Their Implications for Supporting Transformative Governance Practices. *Sustainability*, *16*(10), 3922. https://doi.org/10.3390/su16103922

Contreras, J., Espinola, R., Nogales, F. J., & Conejo, A. J. (2003). ARIMA models to predict next-day electricity prices. *IEEE transactions on power systems*, *18*(3), 1014-1020. https://doi.org/10.1109/TPWRS.2002.804943

Deilami, S., Masoum, A. S., Moses, P. S., & Masoum, M. A. (2011). Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. *IEEE Transactions on smart grid*, *2*(3), 456-467. https://doi.org/10.1109/TSG.2011.2159816

Garcia, R. C., Contreras, J., Van Akkeren, M., & Garcia, J. B. C. (2005). A GARCH forecasting model to predict day-ahead electricity prices. *IEEE transactions on power systems*, *20*(2), 867-874. https://doi.org/10.1109/TPWRS.2005.846044

Gkatzikis, L., Koutsopoulos, I., & Salonidis, T. (2013). The role of aggregators in smart grid demand response markets. *IEEE Journal on selected areas in communications*, *31*(7), 1247-1257. https://doi.org/10.1109/JSAC.2013.130708

Harighi, T., Borghetti, A., Napolitano, F., & Tossani, F. (2024). Flexibility modeling for parking lots with multiple EV charging stations. *Electric Power Systems Research*, *234*, 110732.

Kempton, W., Tomic, J., Letendre, S., Brooks, A., & Lipman, T. (2001). Vehicle-to-grid power: battery, hybrid, and fuel cell vehicles as resources for distributed electric power in California.

Li, R., Wu, Q., & Oren, S. S. (2013). Distribution locational marginal pricing for optimal electric vehicle charging management. *IEEE Transactions on Power Systems*, *29*(1), 203-211. https://doi.org/10.1109/TPWRS.2013.2278952

Lopes, J. A. P., Soares, F. J., & Almeida, P. M. R. (2010). Integration of electric vehicles in the electric power system. *Proceedings of the IEEE*, *99*(1), 168-183. https://doi.org/10.1109/JPROC.2010.2066250

Pirouzi, S., & Aghaei, J. (2019). Mathematical modeling of electric vehicles contributions in voltage security of smart distribution networks. *Simulation*, *95*(5), 429-439.

Ramsay, B., & Wang, A. J. (1997). Electricity spot-price estimator with particular reference to weekends and public holidays. In *The 1997 32 nd Universities Power Engineering Conference, UPEC'97. Part 1(of 2)* (pp. 371-374).

Ranjbar, G. A., Simab, M., Nafar, M., & Zare, M. (2024). Day-ahead energy market model for the smart distribution network in the presence of multi-microgrids based on two-layer flexible power management. *International Journal of Electrical Power & Energy Systems*, *155*, 109663. https://doi.org/10.1016/j.ijepes.2023.109663

Rashidizadeh-Kermani, H., Vahedipour-Dahraie, M., Shafie-Khah, M., & Siano, P. (2020). A regret-based stochastic bi-level framework for scheduling of DR aggregator under uncertainties. *IEEE Transactions on Smart Grid*, *11*(4), 3171-3184. https://doi.org/10.1109/TSG.2020.2968963

Richardson, P., Flynn, D., & Keane, A. (2011). Optimal charging of electric vehicles in low-voltage distribution systems. *IEEE Transactions on Power Systems*, *27*(1), 268-279. https://doi.org/10.1109/TPWRS.2011.2158247

Vahedipour-Dahraie, M., Rashidizadeh-Kermani, H., Shafie-Khah, M., & Catalão, J. P. (2020). Risk-averse optimal energy and reserve scheduling for virtual power plants incorporating demand response programs. *IEEE Transactions on Smart Grid*, *12*(2), 1405-1415. https://doi.org/10.1109/TSG.2020.3026971

Yang, J., He, L., & Fu, S. (2014). An improved PSO-based charging strategy of electric vehicles in electrical distribution grid. *Applied Energy*, *128*, 82-92. https://doi.org/10.1016/j.apenergy.2014.04.047



Authors retain the copyright and full publishing rights.
Published by University of Birjand. This article is an open access article licensed under the Creative Commons Attribution 4.0 International (CC BY 4.0)