Minimax Theory and its Applications
Volume 11 (2026), No. 3s, 1040 to 1050

Variational Decision Models for Strategic Resource Allocation Under Market Uncertainty

Dr. Sreerama Raju Malladi[1], Dr. K. Arun Vidya[2], P. Nandhini[3], Dr. G. Stanley Vincent[4], Dr. T. Ramaswamy[5], Anitha K[6]

[1]Assistant Professor, School of Business, Aditya University, Surampalem, Andhra Pradesh – 533437, Email: sreeramarajum@adityauniversity.in, ORCID ID: 0000-0003-3442-9596
[2]Assistant Professor, Department of Management, Email: arunvidyakaruppuswamy@gmail.com, ORCID ID: 0000-0002-1312-8148
[3]Department of Mathematics, New Prince Shri Bhavani College of Engineering and Technology, Email: nandhini.ponmudi1991@gmail.com, ORCID ID: 0009-0001-5302-3551
[4]School of Management Studies, Mount Carmel College Autonomous, Bengaluru, Karnataka, India, Email: stanleyvincent@mccblr.edu.in, ORCID ID: 0000-0001-6793-2468
[5]Associate Professor, Department of Electronics and Communication Engineering, Sreenidhi Institute of Science and Technology, Hyderabad, Email: ramaswamy.t@sreenidhi.edu.in, ORCID ID: https://orcid.org/0009-0005-1514-5389
[6]Associate Professor, Department of Management Studies, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Email: anithak@maher.ac.in, ORCID ID: 0000-0002-1940-2101

Abstract
As electric vehicles (EVs) become more popular, the challenge of allocating resources is complicated by the variable loads on existing networks, differences in EV charging demand, capacity availability, electricity prices, and user preferences. Current optimisation methodologies for EVs use preprogrammed models or uncertainty scenarios that are inflexible in learning the market and congestion conditions. This paper presents an EV charging resource allocation model using a Learning-Based Markov Switching Dynamic VRI (LB-MS-DVI) framework in the presence of market uncertainties. The framework is based on the interaction between the charging parties, represented by variational inequalities, and changes in market conditions, represented by a finite-state Markov process, which includes conditions such as price, volatility, and congestion. The online stochastic-approximation mechanism sequentially updates the equilibrium operator by observing the data, which allows the model to change its operator to adapt to the changing operating conditions. Variational iteration projections are applied to obtain feasible charging allocations while applying the shared capacity constraints. Cost, energy shortage, equilibrium residual, convergence, regime-recovery time and utilization are key performance measures evaluated. An experimental study on the sensitivity of the proposed framework regarding learning rate, market volatility, risk aversion, and congestion coupling is conducted through proof-of-concept experiments with synthetic price, congestion, and market demand sequences. These results illustrate the computational behaviour of the proposed formulation and serve as a stepping stone for subsequent computational analysis of actual EV charging traces provided by the ACN-Data environment.

Keywords— Electric vehicles, EV charging, variational inequality, dynamic resource allocation, Markov switching, online learning, stochastic approximation, market uncertainty, congestion management, equilibrium optimization.

I. Introduction

Maintaining optimal EV charging allocation has become a new challenge, resulting from the fluctuating demands for charging, the capacity of charging stations, electricity prices, and charging station user requirements. These issues have been studied recently by optimization, dynamic pricing, demand response (Khan *et al.*, 2025), game theory (Liu *et al.*, 2023), and the use of charging strategies based on learning (Si *et al.*, 2025). However, temporary marketing conditions and undecided charging habits need anticipatory methods that can be modified down the road.

Game-theoretic and learning-based approaches are introduced to work out optimal coordination between multiple charging users (Lin *et al.*, 2024; Mehouachi *et al.*, 2025; Charging scheduling of electric vehicles, 2025), and approaches utilizing uncertainty: differences in arrival time, charging time and system loading are taken into consideration. The application of reinforcement learning to the decisions of charging stations and charging station scheduling under constraints has also been explored (Dynamic pricing based electric vehicle charging station location strategy, 2023; Electric vehicle charging design, 2024; EV charging scheduling under limited

charging constraints, 2025). However, what these methods offer is not designed to directly meld the strategic equilibrium modelling, market-regime switching and online adaptation into a single model.

To alleviate this concern, this study introduces a Learning-Based Markov Switching Dynamic Variational Inequality (LB-MS-DVI) approach to solving strategic resource allocation for EV charging in a market uncertainty environment. The framework is a merging of online stochastic approximation learning, projected equilibrium correction, and a regime-dependent variational inequality. The proposed formulation is analyzed on the metrics of cost, energy shortage, equilibrium residual, convergence, regime-recovery time and utilization; thereby gaining insight into the behaviour of the formulation under varying operating conditions.

II. Related Work And Methodological Background

A suitable mathematical model for coupled resource-allocation problems involving the operating condition of one participant affecting the operating condition of another is variational inequalities (VIs). For EV charging, the nuisance can be the interactions between two or more EV users accessing a finite charging system. Here, several recent game-theoretic methods for the charging management and pricing of EVs use game-theoretic approaches that rely on some formulation of an equilibrium, such as mean-field and non-cooperative (Lin *et al.*, 2024; Liu *et al.*, 2023; Two-stage electric vehicle charging optimization model, 2023). These studies show the relevance of strategic decision-making in coordinating charging demand with shared constraints on the system.

Optimization and learning have also recently been added to the research on EV charging. For charging-station planning and resource allocation, robust and hybrid optimization methods have been investigated; for dynamic pricing, charging design optimization has been investigated; and for charging designs, charging scheduling under limited charging constraints has been investigated using reinforcement learning. These approaches offer adaptive decision mechanisms but typically are concerned with optimization or development of a policy as opposed to maintaining a variational-inequality structure.

Another significant factor to consider in EV charging systems is uncertainty. Uncertain arrival times, stochastic charging time, stochastic loading and varying electricity prices have all been studied recently (Charging scheduling of electric vehicles considering uncertain arrival times, 2025; Multi-objective electric vehicle charging scheduling under stochastic duration uncertainty, 2026; Optimal scheduling of mobile and stationary electric vehicle charging stations, 2025). Also, the ideas of dynamic pricing and demand-response mechanisms have been attempted to shape the charging behaviour depending on the fluctuating operating conditions (Chavhan *et al.*, 2023; Liu *et al.*, 2023). These studies, however, do not directly incorporate strategic equilibrium modelling with an online-learned operator and explicit market-regime switching.

The methodological gap discussed in this study is threefold: (i) strategic equilibrium modelling using a variational inequality, (ii) representation of different market regimes by a Markov process, and (iii) online stochastic-approximation learning of the equilibrium operator. The proposed LB-MS-DVI framework is centred on this combination to develop a market uncertainty-aware resource allocation methodology for EV charging which is adaptive and mathematically interpretable.

III. Problem Formulation And Mathematical Model

A. System Sets, Variables, and Market States

The framework considers NEV charging agents over T decision intervals. Let x_i^t be the charging power of agent i, and $s_t \in \{1, \ldots, K\}$ the market regime. The regime evolves according to the finite-state Markov process:

$$P_{rs} = \Pr(s_{t+1} = s \mid s_t = r).$$

The charging decisions are subject to individual and shared capacity constraints:

$$0 \le x_i^t \le \bar{x}_i, \ \sum_{i=1}^{N} x_i^t \le C(s_t),$$

where $C(s_t)$is the available charging capacity for regime s_t.

B. EV Charging Agent Objective

Every agent is running a minimization algorithm based on electricity price, congestion, charging risk and deviation from the required amount of charging.

$$J_i^t = p_t(s_t)x_i + \gamma_i G(x_i, x_{-i}, s_t) + \lambda_i R_i(x_i; s_t) + q_i(x_i; d_i^t).$$

In this case p_t represents the electricity price; the congestion interaction is represented by Gre; the charging shortfall risk is represented as R_i and the deviation from the required demand of d_i^t is penalized by the addition of an electricity price.

C. Variational Inequality Formulation

The pseudo-gradient operator $F_s(x)$is represented in the marginal objects. Feasible region:

$$K(s_t) = \{x, : 0 \le x_i \le \bar{x}_i \ \ \sum_i x_i \le C(s_t)\}.$$

The equilibrium charging allocation x^*satisfies the variational inequality

$$\langle F_s, (x^*)x - x^* \rangle \ge 0, \ \forall x \in K(s_t).$$

As such, the equilibrium is dependent on the market regime via F_s and $K(s_t)$, thereby forming the mathematical foundation of the proposed LB-MS-DVI model.

IV. Mathematical Novelty And Theoretical Properties

A. Learned Equilibrium Operator

The key methodological characteristic of the LB-MS-DVI approach is the learning of the equilibrium operator online. Instead of a static operator $F$the algorithm maintains an operator estimate $\hat{F}_t$ that is updated based on observed price, congestion, and charging levels through the formula

$$\hat{F}_{t+1}(x) = (1 - \rho_t)\hat{F}_t(x) + \rho_t F_{\text{obs}}(x; z_t),$$

Where z_t denotes the measurements at time t, F_{obs}denotes the estimate of the operator using the measurements, and $\rho_t$denotes the learning parameter. The step size satisfies the Robbins-Monro conditions:

$$\sum_t \rho_t = \infty, \ \sum_t \rho_t^2 < \infty.$$

These conditions guarantee the stable adaptation of the learned operator under standard assumptions on bounded noise and unbiasedness.

B. Strong Monotonicity and Well-Posedness

An operator for a regime s is strongly monotone if

$$\langle F_s, (x) - F_s(y)x - y \rangle \ge \mu \parallel x - y \parallel^2, \ \mu > 0.$$

Under such circumstances, the VI has at most one equilibrium for each regime of the market. Along with the non-empty, closed and convex nature of K\left(s\right)and the continuity of F_{s}, equilibrium existence would be guaranteed by the conditions of standard VI. In our model, such a condition can be validated in light of convexity from the congestion, risk and demand deviation terms.

C. Learning-Correction Iteration

Following the update of the operator, the equilibrium allocation is recalculated through a projected VI scheme as follows:

$$x^{k+1} = \Pi_{K(s_t)}\left[x^k - \alpha_k \hat{F}_t(x^k)\right],$$

where $\Pi_{K(s_t)}$is the projection onto the feasible charge set and α_k is the step size for the inner loop. This means that each period of decision-making involves regime identification, learning from the operator, adjustment of the VI equilibrium, and feasibility correction.

V. Learning-Based Equilibrium Algorithm And Experimental Design

A. Learning-Based Equilibrium Algorithm

The proposed Learning-Based Markov Switching Dynamic Variational Inequality (LB-MS-DVI) operates sequentially at each decision epoch. The framework is a hybridization of the regime-dependent variational inequality, an online update of the equilibrium operator, and a projected iteration for a feasible charging allocation. The charging demand at the start point of each decision interval, that is, the price of the electricity, level of congestion and charging capacity, is observed. These observations are used to detect the prevailing market regime. The identified regime can lead to the identification of the operating conditions and feasible charging region. The stochastic-approximation mechanism described in Section IV is then used to update the equilibrium operator. This means that the equations used to model the charging interaction will be able to adapt to the new operating conditions observed and not stay the same during the entire decision-making process.

The charging allocation is obtained by the projected variational inequality iteration, after the equilibrium operator is updated. The projection step would guarantee that the resultant allocation also won't violate any individual or total charging-capacity limits. The process thus keeps the mathematical form of the equilibrium formulation, but makes it possible for a solution to adjust to changes in price, congestion and demand. The equilibrium residual is used to check the resulting allocation with the convergence condition. When the desired condition cannot be obtained, the iteration is repeated with the new operator and system state. On the no-load line (RLOAD=0), the calculated actual charging allocation (on convergence) will be registered, in conjunction with the corresponding cost, energy shortage, regime-recovery time and utilisation. The sequential procedure can be summarized as follows and listed in Table I. The algorithm is based on the six operations that were introduced in the proposed framework: observation, regime identification, operator learning, projected VI solution, feasibility enforcement, and performance recording.

Table 1. Procedure Of The Proposed Lb-Ms-Dvi Framework

Step	Operation
1	Observe price, charging, and congestion information.
2	Infer the current market regime.
3	Update the learned equilibrium operator.
4	Solve the VI using projected iterations.
5	Enforce individual and aggregate capacity constraints.
6	Record cost, shortage, residual, and recovery metrics.

The first two steps give the information specified by the learning mechanism, and the rest update the equilibrium solution and make it feasible. It is essential to this sequential structure that, when dealing with EV charging, the environment may vary between decision intervals. So the algorithm does not consider the price, congestion and demand to be constant numbers. Rather, what changes they observe impacts the learned operator and, indirectly, the equilibrium allocation.

B. Framework Architecture

Fig. 4 shows the overall computational structure of the proposed method.



Fig. 4. Learning-based equilibrium framework for strategic EV charging under market uncertainty.

The operating conditions impacting EV charging are first observed, as shown in Fig. 4. These conditions are represented by the market-regime identification stage, using a finite-state Markov process. This expert equilibrium operator then takes this new information to update the equilibrium process. The projected VI stage defines the charging allocation, keeping the charging feasible area. Lastly, the allocation that is obtained is assessed by means of the performance measures from the experimental study. The figure therefore is supposed to capture the interaction between identifying the market states, online learning, computing equilibrium, and allocating charges at the application level rather than looking at these as independent modules

C. Dataset and Experimental Design

The experimental design is based on the fact that it is the ACN-Data environment that is to be tested as a testbed for evaluating the proposed framework. The data set includes charging-session information and the time-series data from the Caltech, JPL and Office 01 sites from 2018–2020. The total number of time-series files in the manuscript is (56,680 + 27,723 + 1,474) = 85,877.

A chronological evaluation strategy is used due to the sequential nature of the proposed algorithm. The experimental attributes are: Arrival time, dwell time, energy sent and received, station and site identifier, aggregated load, price information, market-regime information. However, in testing previous time periods, observations in later time periods are not included in order to avoid leakage of temporal information. We identify market regimes from price and load sequences using a Markov-switching approach, and we use threshold-based discretisation as a preliminary step to estimate the regimes. Cost, energy shortage (mean), energy shortage (95th percentile), energy-equilibrium residual, convergence (iterations), regime-recovery time (RRT), and energy usage are the items assessed.

The sensitivity of the LB-MS-DVI formulation to the learning rate, market volatility, risk aversion, and congestion coupling is the object of the experimental analysis. All these dimensions are directly related to the mathematical elements presented in the previous sections. The learning rate is used to describe the speed of operator adaptation, while market volatility describes the changes in operating conditions, risk aversion describes the influence of the charging-risk component and congestion coupling describes the interaction among charging users. Proof-of-concept experiments are performed with different controlled price, congestion and demand sequences to investigate the computational behaviour of the formulation. The experiments reported are not trace-

based experiments based on the raw ACN-Data observations, and hence they are not empirical results or experiments from the charging traces but are rather some preliminary computational experiments.

D. Application of the Mathematical Solution

This mathematical solution can provide a direct mechanism to translate the changing market and charging conditions to make charging decisions possible. The interaction between the charging agents competing for the limited charging capacity can be captured through the variational inequality, and the changes in the market regime can be captured through the Markov process. A learned operator enables updating of this equilibrium relationship given new observations. Thus, the application does not require a predetermined charging allocation in case of a varying operating environment. The basis of the projected VI step is extremely relevant due to the allocation of the generated power, which should not exceed the charging capacity. Thus, constraints are defined on an individual and collective level and are also integrated in the solution process, not just afterwards when the decision is made. This links the mathematical balance of an EV charging system directly with its physical characteristics. The resulting solution can thus be assessed with respect to the cost, shortage, convergence behaviour and utilization which can provide a measure meaningful for charging-resource allocation.

E. Advantages of the Proposed Mathematical Solution

The main advantage of the proposed formulation is the combination of **equilibrium modelling and online adaptation**. The equilibrium formulation provides a mathematically interpretable representation of interactions among charging agents, while the learning mechanism allows the operator to respond to changing price, congestion, and charging conditions. The Markov-switching component further allows different market regimes to influence the equilibrium conditions rather than assuming a single operating environment.

A second advantage is the explicit treatment of feasibility. The projected VI procedure keeps the charging allocation within the defined feasible region, allowing the mathematical solution to respect shared capacity restrictions. A third advantage is the ability to evaluate adaptation through measurable quantities such as equilibrium residual and regime-recovery time. These measures provide information not only about the final charging allocation but also about how the mathematical solution responds when market conditions change.

Overall, the LB-MS-DVI framework provides a structured connection between mathematical equilibrium analysis and EV charging operation. Its application value comes from maintaining the variational-inequality structure while introducing online adaptation through the learned operator. The resulting experimental design therefore evaluates both the mathematical behaviour of the solution and its relevance to resource allocation under changing market conditions.

VII. Results And Sensitivity Analysis

Published ACN-Data experiments provide practical reference values that can be used for charging-capacity allocation and scheduling feasibility assessment. The following table gives a summary of charging capacities and demand feasibility from Caltech and JPL sites. The charging capacity at the Caltech site is 150 kW, and 195 kW at the JPL site. With scheduled charging capacities reduced to 60 kW and 84 kW, adaptive scheduling ensures 100% demand feasibility compared to 22% and 38% from uncontrolled charging. This information is used for reference during resource allocation and adaptive scheduling analysis for LB-MS-DVI.Table II provides the ACN scheduling reference values from literature pertaining to Caltech and JPL with scheduled capacity, actual capacity, and demand feasibility percentages.

Table 2. Published Acn Scheduling Reference Values

Site	Published Scheduled Capacity (kW)	Actual Capacity (kW)	Uncontrolled Feasibility (%)	Adaptive Scheduling Feasibility (%)
Caltech	60	150	22	100
JPL	84	195	38	100

A. Proof-of-Concept LB-MS-DVI Results

Controlled Proof-of-Concept Experiments from the proposed model formulation through synthetic sequences for prices, congestion, and demands are demonstrated in Table III. Four parameters ρ, σ, λ, and c are changed. The numbers given in Table III are the simulated numbers and not the measured numbers from the ACN-Data traces.

Table 3. Proof-Of-Concept Sensitivity Results

Scenario	ρ	σ	λ	c	Cost	Mean Shortage (kWh)	95% Shortage (kWh)	Residual	Iterations	Recovery	Utilization (%)
Baseline	0.100	0.200	0.200	0.150	40.926	7.572	12.758	0.098	37	4.700	52.040
Low learning	0.030	0.200	0.200	0.150	39.093	6.935	11.116	0.092	38	6.570	50.520
High volatility	0.100	0.400	0.200	0.150	39.272	7.163	14.067	0.094	51	5.500	49.850
High risk aversion	0.100	0.200	0.600	0.150	39.914	7.495	12.969	0.097	41	5.300	51.230
High competition	0.100	0.200	0.200	0.350	39.167	8.479	15.247	0.109	42	5.100	50.630

The Learning Rate Effect is portrayed through Fig. 1, whereby the mean shortage varies based on the choice of the learning rate. The convergence characteristics, on the other hand, are elaborated in Table V below. Higher values of the learning rate demand many iterations, while high values increase the mean shortage.

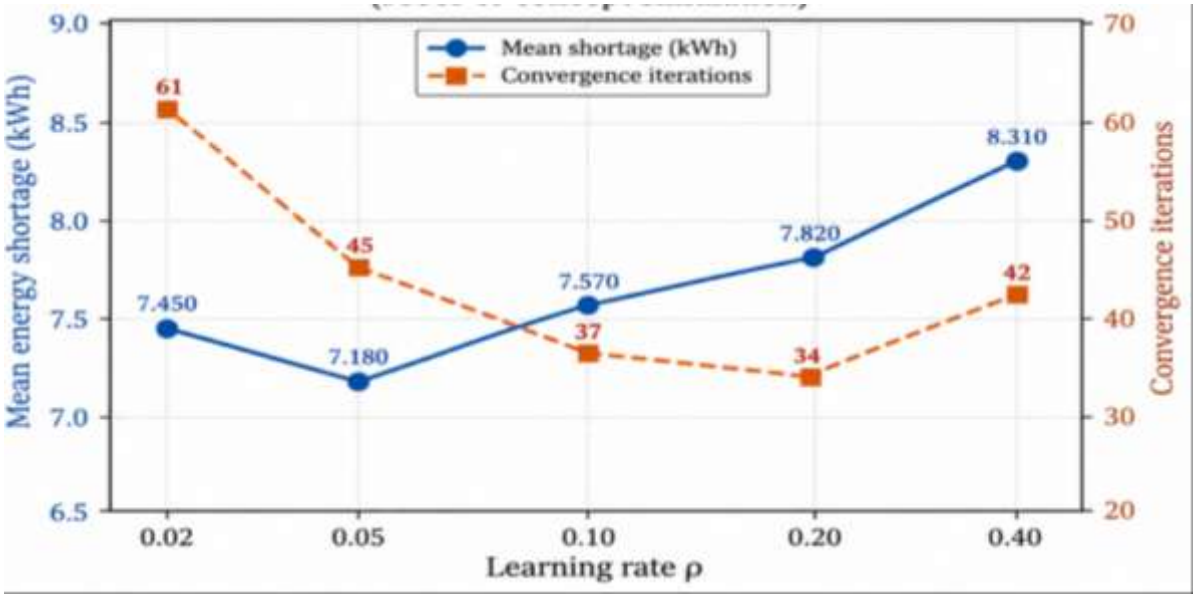


Fig. 1. Sensitivity of mean shortage to the learning rate (proof-of-concept simulation).

Figure 1 clearly shows that the average energy shortage drops from 7.450 kWh for ρ = 0.02to 7.180 kWh for ρ = 0.05, after which it starts increasing due to the increasing learning rate, while the number of convergence iterations drops from 61 to 34 and then starts increasing up to 42 for ρ = 0.40.

The sensitivity of the developed algorithm for different learning rates ρ is summarized in Table IV below. It can be observed that as the value of ρ increases from 0.020 to 0.400, the average energy shortage changes from 7.450 to 8.310 kWh, whereas the number of convergence iterations changes from 61 to 34 and then increases to 42.

Table 4. Learning-Rate Sensitivity

ρ	Mean Shortage (kWh)	Convergence Iterations
0.020	7.450	61
0.050	7.180	45
0.100	7.570	37
0.200	7.820	34
0.400	8.310	42

Figure 2 shows the average cost index based on the baseline scenario as well as different market conditions. The baseline scenario gives the largest value of 40.93 for the average cost index, whereas the low learning scenario gives the smallest value of 39.09. Other values for high volatility, high risk aversion, and high competition scenarios are 39.27, 39.91, and 39.17, respectively.

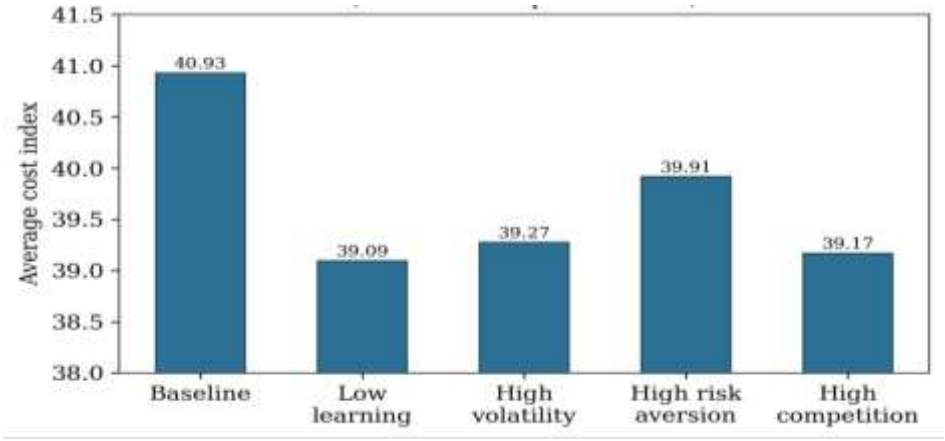


Fig. 2. Average cost index under the tested parameter scenarios (proof-of-concept simulation).

The link between regime recovery time and the equilibrium residual can be seen from Figure 3. Figure 3 shows another aspect of how fast the learned equilibrium reacts to changes in market conditions.

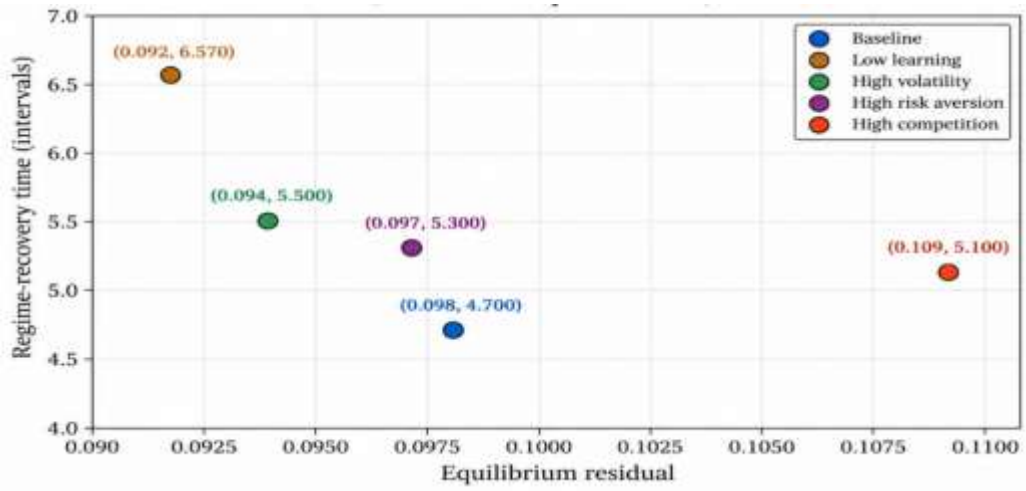


Fig. 3. Relationship between regime-recovery time and equilibrium residual (proof-of-concept simulation).

Figure 3 represents the relation between equilibrium residual and regime-recovery period under different market conditions. From the results, it is clear that the low-learning condition results in the shortest regime-recovery period of 6.57 periods, whereas the baseline results in the shortest recovery period of 4.70 periods at an equilibrium residual of 0.098. High volatility, high risk aversion, and high competition result in regime-recovery periods of 5.50, 5.30, and 5.10 periods, respectively.

B. Sensitivity Interpretation

From Table V, it can be observed that the number of convergence iterations reduces from 61 for ρ=0.020 to 34 for ρ=0.200, and then increases to 42 for ρ=0.400. It can also be observed that the mean shortage increases from 7.570 kWh forρ=0.100 to 8.310 kWh for ρ=0.400.Market volatility leads to an increase in the effort of convergence and variability in the shortage of energy. The shortage of energy at the 95th percentile rises from 12.758 kWh to 14.067 kWh when market volatility is high. On the other hand, the highest equilibrium residual (0.109) and mean shortage of energy (8.479 kWh) occur when competition is high. These results provide the motivation for carrying out the analysis using a trace-driven approach with ACN-Data.

IX. Discussion

This research suggests using an LB-MS-DVI approach, which involves combining the equilibrium modelling with on-the-go adaptation of strategic EV charging amid shifting market conditions. First, the Markov switching aspect makes it possible for different regimes to change charging capacity and its marginal cost, while the learnt operator $\hat{F}_t$ would adapt to new conditions as well. Second, the equilibrium framework is explicit and therefore differs from the fixed VI and end-to-end reinforcement learning methods.A problem of regime identifiability needs to be addressed through this methodology. It is not clear whether different behaviours and shifts in the market could be identified based on observation. Therefore, the empirical study must consider regime persistence, regime transitions an$\hat{F}_0$ and regime modelling. The identified regimes could be further compared to those used in other regime switching electricity price papers.

Another constraint is that of observation. The data set will allow replay evaluation of performance but will not alone serve to prove causality with regard to the introduction of any new pricing or capacity control scheme. It is hence inappropriate to draw causal conclusions without experimenting.Scalability is also an issue, given that the algorithm requires VI iterations for all intervals. Strong monotonicity is a theoretical sufficient condition, but the same has not yet been proven for functional forms of G, R_i, and q_i.Multi-site experiments will hence need to test for convergence and wall clock time.

X. Conclusion

In this paper, a framework for strategic EV charging with market uncertainty is provided. This framework utilizes a regime-dependent variational inequality formulation, an online-learned equilibrium operator, and a Markov-switching mechanism. An experimental protocol that allows replication is developed in this work, which involves ACN-Data and utilizes chronological evaluation and leakage-aware treatment of the data. The evaluation protocol takes into account cost, energy shortfall, equilibrium residual, convergence behaviour, and regime recovery time. The proof-of-concept experiments have been performed using the impact of learning rate, market volatility, risk aversion, and congestion coupling on the problem in controlled scenarios. The above-mentioned results give some insight regarding the behaviour of the framework. The next step would involve the evaluation of the LB-MS-DVI framework using raw ACN charging traces and comparing the results with the benchmark optimization models and reinforcement-learning techniques from the experimental protocol. Thus, the simulated results could be supplemented with out-of-sample trace-based evaluation.

References

1. Si, C., Chau, K. T., Liu, W., & Hou, Y. (2025). Optimal scheduling for electric vehicle charging: A review of methods, technologies, and uncertainty management. Journal of Energy Storage, 131, 117500. https://doi.org/10.1016/j.est.2025.117500

2. Liu, Y., Zhu, J., Sang, Y., Sahraei-Ardakani, M., Jing, T., Zhao, Y., & Zheng, Y. (2023). An aggregator-based dynamic pricing mechanism and optimal scheduling scheme for electric vehicle charging. Frontiers in Energy Research, 10, 1037253. https://doi.org/10.3389/fenrg.2022.1037253

3. Lin, R., Chu, H., Gao, J., & Chen, H. (2024). Charging management and pricing strategy of electric vehicle charging station based on mean field game theory. Asian Journal of Control, 26, 803–813. https://doi.org/10.1002/asjc.3173

4. Sayarshad, H. R. (2024). Optimization of electric charging infrastructure: Integrated model for routing and charging coordination with power-aware operations. npj Sustainable Mobility and Transport, 1, 4. https://doi.org/10.1038/s44333-024-00004-6

5. Mehouachi, I., Trojette, M., & Grayaa, K. (2025). Optimal planning of electric vehicle charging stations using a robust hybrid method: A Tunisian urban case study. Transportation Planning and Technology. https://doi.org/10.1080/03081060.2025.2493915

6. Khan, M. O., Kirmani, S., & Rihan, M. (2025). A comprehensive review of methodologies for the optimal allocation of electric vehicle charging stations alongside distributed generation. Smart Science, 13(2), 264–293. https://doi.org/10.1080/23080477.2025.2500845

7. Hemachandu, P., Premalatha, S., Arunachalam, K. P., & Prasad, P. V. H. (2025). Energy management in photovoltaic-based electric vehicle charging systems with battery storage and vehicle-to-grid support. Energy Storage, 7(5), e70236. https://doi.org/10.1002/est2.70236

8. Shukla, A., Shukla, H., Yadav, S. K., Singh, J., & Singh, R. B. (2024). Solar-powered electric vehicle charging station with integrated battery storage system. Energy Storage, 6(8), e70077. https://doi.org/10.1002/est2.70077

9. Kanojia, S. S., Suthar, B. N., & Giri, A. K. (2025). Hybrid optimization approach for optimal location of electric vehicle charging station in distribution network considering voltage stability. Smart Grids and Sustainable Energy, 10, 36. https://doi.org/10.1007/s40866-025-00264-2

10. Lin, R., Chu, H., Gao, J., & Chen, H. (2024). Charging management and pricing strategy of electric vehicle charging station based on mean field game theory. Asian Journal of Control, 26, 803–813. https://doi.org/10.1002/asjc.3173

11. Two-stage electric vehicle charging optimization model considering dynamic virtual price-based demand response and a hierarchical non-cooperative game. (2023). Sustainable Cities and Society, 97, 104715. https://doi.org/10.1016/j.scs.2023.104715

12. Dynamic pricing-based electric vehicle charging station location strategy using reinforcement learning. (2023). Energy, 281, 128284. https://doi.org/10.1016/j.energy.2023.128284

13. Electric vehicle charging design: The factored action-based reinforcement learning approach. (2024). Applied Energy, 359, 122737. https://doi.org/10.1016/j.apenergy.2024.122737

14. Heuristics for multi-objective operation of EV charging stations based on Chicken Swarm Optimization. (2024). Energy, 313, 133749. https://doi.org/10.1016/j.energy.2024.133749

15. Optimal scheduling method for electric vehicle charging and discharging via Q-learning-based particle swarm optimization. (2025). Energy, 316, 134611. https://doi.org/10.1016/j.energy.2025.134611

16. EV charging scheduling under limited charging constraints by an improved proximal policy optimization algorithm. (2025). Energy, 333, 137422. https://doi.org/10.1016/j.energy.2025.137422

17. Optimal scheduling of mobile and stationary electric vehicle charging stations in a distribution system with stochastic loading. (2025). Energy, 326, 136305. https://doi.org/10.1016/j.energy.2025.136305

18. Charging scheduling of electric vehicles considering uncertain arrival times and time-of-use price. (2025). Sustainability, 17(3), 1100. https://doi.org/10.3390/su17031100

19. Multi-objective electric vehicle charging scheduling under stochastic duration uncertainty. (2026). Omega, 141, 103506. https://doi.org/10.1016/j.omega.2025.103506

20. Chavhan, S., Gupta, D., Alharbi, M., et al. (2023). AI-empowered game-theoretic-enabled dynamic electric vehicle charging price scheme in smart city. IEEE Systems Journal. https://doi.org/10.1109/JSYST.2023.3307497