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Elektrikli Araçlar için Gerçek Trafik Bilgilerini Dikkate Alan Dinamik Fiyatlandırma Tabanlı Enerji Yönetim Modeli

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Özet

Elektrikli araçların kullanımının yaygınlaşmasıyla birlikte artan şarj talebi, elektrik dağıtım şebekesinde yük dengesizliği, ani yük değişimleri, harmonikler ve gerilim dalgalanmaları gibi negatif etkilere yol açmaktadır. Ayrıca şarj talebinin düzensiz olması elektrikli araç kullanıcı konforunu ve trafik yönetimini de etkileyen negatif bir durumdur. Bu çalışmada, bu negatif durumları ortadan kaldırmak amacıyla şehir içi elektrikli araç şarj altyapısında kullanılmak üzere geliştirilen dinamik fiyatlandırma tabanlı bir enerji yönetim modeli sunulmaktadır. Bu bağlamda önerilen model, fiyatı yalnızca ekonomik bir çıktı olarak değil aynı zamanda şebeke yük dengesini yönlendiren bir kontrol değişkeni olarak ele almaktadır. Modelde dört temel giriş parametresi (trafik, istasyon doluluk oranı, konum ve araç şarj seviyesi) vardır ve her iterasyonda dinamik bir şekilde güncellenmektedir. MATLAB ortamında geliştirilen model, Google Maps API aracılığıyla elde edilen gerçek trafik verileriyle desteklenmiş ve on iterasyon boyunca test edilmiştir. Sonuçlar, geliştirilen modelin düşük şarj seviyesine sahip araçları önceliklendirdiğini ancak bunu yaparken de şebeke yükünü dengeli biçimde gözettiğini göstermektedir. Ayrıca, yüksek doluluk oranına sahip istasyonlarda fiyat artışı gözlenmiş ve bu durumda kullanıcıların daha düşük doluluk oranına sahip istasyonlara teşvik edildiği görülmüştür. Çalışma, fiyatlandırmanın yalnızca ekonomik değil aynı zamanda sistemsel verimlilik açısından da bir karar değişkeni olarak kullanılabileceğini ortaya koymaktadır. Gelecek çalışmalarda model, yapay zekâ ve optimizasyon tabanlı yöntemlerle genişletilebilme ve test sistemleri yardımıyla enerji ve ulaşım sistemlerindeki problemlere çözüm olarak kullanılabilme potansiyeline sahiptir.

Anahtar kelimeler: Elektrikli araçlar, Dinamik fiyatlandırma, Enerji yönetimi, Şebeke, Ulaşım sistemleri

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Dynamic Pricing-Based Energy Management Model for Electric Vehicles Considering Real Traffic Information

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Abstract

Increasing charging demand with the widespread use of electric vehicles leads to negative effects such as load imbalance, sudden load changes, harmonics and voltage fluctuations in the electricity distribution network. Furthermore, irregular charging demand negatively impacts electric vehicle user comfort and traffic management. This study presents a dynamic pricing-based energy management model developed for use in urban electric vehicle charging infrastructures to address these challenges. The proposed model considers price not only as an economic output but also as a control variable that manages grid load balance. There are four input parameters (traffic, station occupancy rate, location and state of charge) in the pricing model and these parameters are dynamically updated at each iteration. The model was developed in MATLAB environment and was employed real-time traffic data obtained through the Google Maps API. The model tested for ten iterations. The results show that the pricing model prioritizes low charge levels vehicles. But the model maintaining balanced grid load simultaneously. Furthermore, price output increases high occupancy rates charging stations in order to encourage users to choose stations with lower occupancy rates. Results of this study demonstrates that pricing mechanism can be used as a decision variable both economic reasons and system efficiency. In future works, the model might be extended with artificial intelligence and optimization-based methods. Pricing model serves as a potential solution to challenges in energy and transportation networks with the help of test systems.

Keywords: Electric vehicles, Dynamic pricing, Energy management, Grid, Transportation systems

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1. Introduction

The widespread adoption of electric vehicles (EVs) presents a significant opportunity for the development of sustainable and environmentally friendly transportation systems [1,2]. EVs reduce greenhouse gas emissions and reliance on fossil fuels and they contribute to environmental sustainability by increasing energy efficiency [3,4]. However, there is a quick transition to EV usage in recent years and this has led to increases in energy demand which negatively impacting distribution systems [5,6]. Although the charging infrastructure has been improving recently, the capacity of charging stations remains insufficient to handle the growing EV charging load especially in urban areas [7]. According to the official statistics published by the Energy Market Regulatory Authority (EPDK), as of July 2025 there are 32,682 publicly accessible EV charging sockets in Türkiye, while the total number of registered EVs has reached 291,775, highlighting the increasing pressure on charging station capacity despite the rapid expansion of the infrastructure. [8]. EV charging load can cause technical challenges on the distribution grid such as sudden load changes, harmonics and voltage fluctuations [9-11]. This situation is negatively affecting not only the stability of energy systems but also traffic management systems and user satisfaction [12,13].

The charging load management of EVs is important research area for energy and transportation systems [14,15]. In recent years, studies in the literature focus on several key strategies including charging scheduling algorithms [16,17], routing algorithms [18,19], smart grid-based strategies [20,21], charging demand [22,23] and dynamic pricing mechanisms [24,25]. These strategies are using in order to balance power grid load with affecting EV user behavior in the peak energy demand periods. Dynamic pricing methods is one of the most effective approaches among these key strategies because it integrates variables such as real-time traffic, charging station occupancy rate, locations of station and vehicle and state of charge (SoC) into the pricing process [26]. Dynamic pricing strategy works as a mechanism to both guide user behavior and support grid load balance by managing energy demand and grid load according to real-time conditions [27,28].

In this study, a dynamic pricing-based energy management model was developed. Model evaluates input parameters such as traffic, station occupancy rate, location and SoC. Main purpose of the model is to optimize EV user comfort and the grid balancing objectives of the DSO. In this regard, price parameter is considered both economic outcome and control variable that affects system balance. The model was developed in MATLAB environment. Tests has been made in a simulation-based environment and optimization or artificial intelligence methods were not used. The purpose at this point was show both the basic operation of the price estimation mechanism and the interaction between variables. The model was executed under simple scenarios in order to show the logical consistency of the dynamic pricing system. The model's strong sides are its ability to work with real-time traffic data which received from the Google Maps API and the dynamically changing input parameters. At each iteration traffic, station occupancy rate, location and SoC parameter are dynamically updating and this allow the system to reflect real-time urban conditions.

Although multi parameter pricing models considering factors such as traffic, distance, occupancy and SoC have been investigated in the literature, the proposed model stands out in two main aspects. First, real-time traffic and distance information are directly obtained from the Google Maps API, enabling the pricing mechanism to reflect actual urban mobility conditions rather than synthetic or static data. Second, the price is treated not only as an economic output but also as a control variable to influence charging demand distribution among stations. These allow the model to operate dynamically updated energy management mechanism for urban EV charging infrastructures.

The model aims to balance EV charging demand and load on the distribution grid with the help of dynamic pricing algorithm. Structure of the model, key assumptions and parameters are presented in the Material and Methods section. Performance of the model are evaluated in detail and effects of input parameters on pricing outcomes are presented in the Results and Discussion section. Finally, findings are presented and overall assessment is provided and possible future works (in order to develop model with optimization and artificial intelligence methods) are discussed in the Conclusion section.

2. Material and Methods

In this study, a dynamic pricing-based energy management mechanism was developed for use in urban EV charging infrastructures. The model was designed to simultaneously consider both EV user comfort and the DSO's grid-balancing objectives. In order to achieve this, a real-time model was created in which the input parameters (traffic, station occupancy rate, location and SoC) are dynamically updated, while the output parameter is price.

The model was developed in MATLAB and all calculations, data flow and iterative updates were conducted on this platform. The MATLAB license provided by Fırat University was used. No optimization algorithms or artificial intelligence-based methods were used during model creation or price estimation. MATLAB was chosen due to its flexibility in simulating and numerically modeling multivariable systems. In this study, MATLAB was used both to integrate real-world traffic and location data from the Google Maps API into the system and to calculate dynamically updated parameters at each iteration. As a result, the system extends beyond a random simulation and gain a real-time, data-driven structure.

In the Dynamic Pricing-Based Energy Management Model subsection, the structure of the system, its iterative working principle, interaction with traffic data and the role of price as a control variable are explained. The Model Assumptions section describes elements such as time definition, traffic and charging dynamics, station occupancy rate and system constraints. Finally, the Model Parameters subsection details the influence of each variable on pricing and explains the general operation of the price estimation mechanism. This structure enables the model operates by both monitoring dynamically changing urban transportation conditions and adjusting the load balance of charging stations based on price. Thus, the proposed system has the potential to work as a dynamic, dual-purpose decision support mechanism based on real-time traffic data.

Dynamic pricing-based energy management model

The dynamic pricing-based energy management model developed in this study provides a multi-criteria decision support mechanism designed for urban EV charging infrastructures. The model simultaneously considers both EV user comfort and the DSO's grid-balancing objectives. The input parameters of the model are traffic, station occupancy rate, location and SoC, while the output parameter is price. The structure of the dynamic pricing-based energy management model is presented in Figure 1. The main objective of the model is to develop a real-time price estimation mechanism that enables dynamic evaluation of charging demand based on time-dependent variables. In this approach, price is considered both an economic parameter and control variable that manages the charging load.

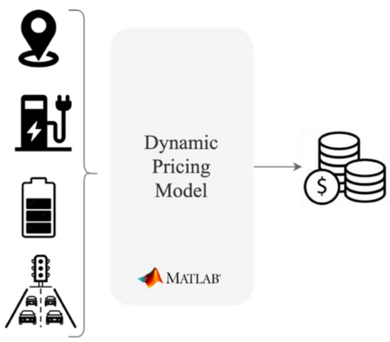

Figure 1. Structure of the dynamic pricing-based energy management model

As illustrated in Figure 1, traffic, station occupancy rate, location and SoC are provided as inputs to the dynamic pricing-based energy management model, where their effects are aggregated through the pricing function. The resulting price output influences the distribution of charging demand among stations, thereby indirectly affecting station occupancy levels in subsequent iterations.

The pricing model is consisting of four charging stations and 16 EVs and it operates on urban charging scenarios. The simulation was run on MATLAB for 10 iterations and the state of the system was evaluated at each step. The starting SoC values of the vehicles are randomly given between 10% and 100%. Vehicles are removed from the system and replaced by new vehicles with new SoC values and location when their SoC values reach %100. This keeps constant the number of vehicles in the system, but traffic, station occupancy rate and energy demand change dynamically.

In the location process of the model, Istanbul was chosen as the study area. Istanbul has high traffic density and large number of charging stations. This makes it a suitable testing city for dynamic pricing scenarios. The locations of the vehicles and charging stations were determined in a realistic latitude–longitude range. This reflects the urban distribution and ensuring that stations were neither too close to each other nor located in inaccessible areas. Thanks to this, model was developed on a geographical scenario which realistically reflects urban mobility and the spatial diversity of the charging infrastructure. For each vehicle, range and traffic time to all stations were received from Google Maps API. This allowed the system operate based on real-time traffic conditions.

One of the input parameters, charging station occupancy rate are dynamically updated between 20% and 100% at each iteration. This rate is a normalized value which representing the density of use relative to the station's capacity. Another input parameter, vehicle locations are also updated sensitively to traffic time. For example, vehicles with light traffic cover more distance in the next iteration, while vehicles with heavy traffic move more limited. Similarly for another input parameter, the SoC parameter increase rate of vehicles is modeled according to a realistic charging curve. For example, fast charging behavior is simulating until 80% and then slow charging behavior is simulating after 80%. Therefore, all input parameters are updated iteratively in consistent and interdependent manner. This ensuring that the pricing model retains its dynamic and realistic structure.

In this section, the dynamic pricing-based energy management model was explained in order to demonstrate the conceptual structure of charging management process. However, its correct operation requires it to be based on some physical and operational assumptions. Thus, basic assumptions of the system were detailed in the following section. Scope and limitations of the model and how the parameters are interpreted was explained. These assumptions important because they both strengthen compatibility of the model with real-world conditions and enhance the understandability of the simulation.

Model assumptions

The accuracy of the model depends not only on the operation of its parameters but also on the physical and operational assumptions on which these parameters are based. These assumptions ensuring both the interpretability of the model and its consistency with real-world conditions by determining the limits of the general system. This section explains the basic assumptions considering time, vehicle movement, station occupancy rate and the overall operation of the system. This provides detailed explanation about the structure of the model and the logic behind its behavior in the simulation.

In this model, time is not defined by a fixed time step in the classical sense. The time is modeled which are dynamically updated according to the current state of the system at each iteration. Each iteration is a decision step and all input parameters (station occupancy rate, location, traffic and SoC) are updated dynamically and simultaneously at each iteration. The model does not work in the constant time step (every 10–15 minutes). Rather, there are its own time dynamics based on the update period of API calls, the variability of traffic data and the rate of SoC increase. This approach allows for both more flexible system operation and dynamic and realistic modeling of charging load management.

In the model, traffic data are received from the Google Maps API. Thus, each iteration becomes not only a series of events where parameters are randomly updated, but also an iterative process where real-world data is reflected in the model. All input parameter was dynamically updated at the beginning of each iteration. Vehicle SoC values are updated, station occupancy rates are dynamically changed by model and real-time distance and traffic data are obtained for all vehicle-station pairs via API calls. This structure transforms each iteration of the model into a real-time system assessment representing the current state of urban conditions. In the model, locations of vehicles changes related to urban traffic conditions at each iteration. While vehicle displacement is limited in areas with high traffic, vehicles are allowed to travel longer distances in areas with calm traffic. This mechanism allows the model to work both in terms of charging status and price prediction and as an urban mobility simulation encompassing traffic related behaviors. This provides a mobility behavior that is compatible with the dynamic urban mobility and represents the interaction of the charging infrastructure with traffic in a more realistic way.

The station occupancy rate parameter used in this study is not a direct physical quantity, but a normalized indicator representing the current station usage intensity. While this representation does not include physical details of the grid infrastructure (busbar loads, transformer capacities or socket numbers), it is used to analyze the operation of dynamic pricing strategies.

The grid load balancing objective in this study is considered at the charging station demand level rather than at the physical electrical network level. The proposed model does not include an power flow analysis or electrical grid topology. Instead, grid related impacts are interpreted indirectly through changes in charging demand distribution among stations driven by the dynamic pricing mechanism. Therefore, the model focuses on demand side load balancing at the charging infrastructure level. The integration of detailed electrical grid models and power flow analysis is considered as future work.

Since the goal at this stage of the model is to evaluate the relative impact of occupancy on price, stations are assumed to have equivalent service capacity. However, in future studies, this structure can be integrated into platforms or test systems suitable for power flow analysis and occupancy rates can be related to real-time busbar loads. This way, the model can become a comprehensive energy management model that includes not only price prediction but also power flows on the grid.

The occupancy rate is dynamically updated at each iteration and this variable acts as a deterrent or incentive in the price prediction function. High occupancy values reflect situations where the station is more likely to wait, while low occupancy rates represent easy access opportunities. The pricing system increases prices at busy stations while reduces prices at stations with available capacity. With this way, the model directing demand and contributing to a balanced distribution of the charging load.

The primary objective of the model developed in this study is to analyze the operation of the dynamic price estimation mechanism. Therefore, technical differences about to EVs (battery power and charging standards) and charging station types (battery capacity, charging curve, power level and charging standard) are not considered in the model. It is assumed that all vehicles have similar battery capacity and charging characteristics and charging stations have equivalent service capacity. This approach enables the model can operate independently of complex technical differences. This allows for a simple analysis of the basic dynamics affecting the pricing mechanism.

The vehicle profiles in the model can be assumed to represent EVs focused on urban use, with a battery capacity of approximately 50–60 kWh and an average range of approximately 300 km. Thanks to this assumption, charging times and energy consumption patterns in the model is similar to typical real-world user behavior. Fast charging stations are widely used in urban charging infrastructures. That's why the model is designed with fast charging stations. They allow for realistic representation of changes in occupancy rates, charging curves and charging cycles.

As a result, these assumptions make the model consistent with real-world conditions and enables for analysis of the effects of the dynamic pricing mechanism. After determining the model's physical foundations and behavioral assumptions, it is necessary to define the variables that influence the price estimation mechanism. In this context, input parameters and output parameter are described in the following section.

Model parameters

In the model developed in this study, the dynamic pricing mechanism is considering several variables to operate. This section defines the four input parameters (traffic, station occupancy rate, location and SoC) and the output parameter (dynamic price value) of the model. Every input parameter of the pricing model is important because they play a critical role in representing key components of the urban charging infrastructure. These parameters influence both EV user behavior and the charging load balance of the distribution grid. An overview of the dynamic pricing-based energy management model is provided in this section. The roles of every parameter and their interactions are explained.

In this model, the station occupancy rate is a normalized component which representing availability capacity of the charging station. On the other hand, technical parameters which relate to the charging or electrical infrastructure (number of sockets or transformer load) are not used in the model directly. Instead, charging station occupancy is considered as demand intensity and the grid managing potential. Station occupancy rate is not modeled based on socket type or busbar load. Rather on the percentage usage rate. This rate shows the current usage situation of the charging station and it allows to be evaluated those stations of different capacities and standards on a common scale. As charging station occupancy rate increases the price value also rises because of the model dynamics. With this, the model can encourage EV users to choose most available stations and can support to balance load distribution across the grid. This parameter is important because it can directly affect both user experience and grid efficiency. Furthermore, charging station occupancy rate parameter has the highest weight among the input parameters of the dynamic pricing-based energy management model. Therefore, the pricing model consider this parameter more than the others while making price estimation.

One of the input parameters of the model, the location parameter is important because it represents the actual driving distance between a vehicle’s current position and the target charging station, based on real road routes. As the distance increases, transportation costs, time losses and energy consumption are expected to increase, leading to an increase in price. Thus, the model considers not only traffic density but also the overhead created by distance. Distances are measured in kilometers at each iteration and information from API data is normalized and incorporated into the price function. Distance serves two fundamental roles in the system. First, as a physical quantity that indirectly affects transportation costs and energy consumption and second, as an optimization variable that increases price sensitivity in demand management. Thus, the model considers distance as a strategic input for energy efficiency and user guidance.

One of the primary strengths of the dynamic pricing-based energy management model is its use of real-time traffic data. Vehicle access conditions to charging stations are calculated based on current traffic density within the urban transportation network. Thus, the model considers the actual travel time between two geographical locations, rather than synthetic or hypothetical values. This allows the price estimation mechanism to have a dynamic and realistic structure that responds to the urban traffic, unlike static approaches. Traffic duration is defined as a time-varying environmental variable in the model. This parameter represents the travel time between vehicle-station pairs in minutes and is updated via the Google Maps API at each iteration. Thus, the model acquires a stochastic structure dependent on external inputs. Traffic duration is used as a weighting factor in the price function, affecting the dynamic state of the system. High traffic periods are the situation which directly increase the price function. This situation direct EV users to alternative charging stations and contribute to demand balancing.

SoC parameter expresses the current battery charge rate as percentage (%) of the EV. The model updates SoC parameter at each iteration by considering the charging curve. In the model, SoC parameter is important both vehicle prioritization and price function personalization for each EV user. The model is thinking high priority charging requests vehicles with low SoC levels, while vehicles with high SoC levels reduce demand elasticity. Among the input parameters the SoC is the only parameter which represent EV user behavior in the pricing model. Thanks to this representation, the model considers both infrastructure factors and individual demand dynamics based on energy requirements.

Variables such as traffic, station occupancy, location and SoC can cause real-time fluctuations in charging demand. In order to manage this situation, dynamic pricing is used to balance demand and optimize energy distribution. In this study, pricing is designed not only as an economic value but also as a control mechanism that guides user behavior. The pricing model normalizes all input parameters and gives them weights with λ values. Then, it produces a dynamic price estimate from the combination of these parameters as the output. As a result, the price is sensitive not only to the measured conditions but also to the λ values that determine the importance of each parameter. This approach enables the model can update itself with dynamically changing conditions. Thus, pricing model balances distribution of charging demand and supports grid load management. The price estimation mechanism is developed using λ weights. These weights representing the influence of four main variables:

- ✓ λ_1: Charging station occupancy rate,
- ✓ λ_2: Location,
- ✓ λ_3: Traffic,
- ✓ λ_4: State of charge (SoC).

The initially determined λ values (λ_1=0.5, λ_2=0.2, λ_3=0.3, λ_4=0.2) represent the initial sensitivities of the parameters relative to each other. At each iteration, these parameters are normalized and considered in the price estimation function, producing price values in the 0–1 range.

The weighting coefficients (λ_i) were selected based on heuristic considerations reflecting the relative importance of each parameter in urban charging scenarios. In particular, charging station occupancy was assigned a higher weight due to its direct impact on congestion, bus load and waiting time, while distance and traffic duration were assigned moderate weights. The SoC related term was included to prioritize low charge vehicles without dominating the pricing mechanism. The primary objective of this study is to demonstrate the operational behavior and internal consistency of the proposed dynamic pricing-based energy management model rather than to optimize the weighting coefficients. A systematic sensitivity analysis and data driven optimization of the λ values will be addressed in future studies.

Restricting the resulting price value to a range of 0–1 prevents both negative and excessively high price values, ensuring the system operates in balance. The purpose of the normalization process is to ensure that all parameters are evaluated on the same scale. The price parameter must be calculated to represent both user comfort and grid balancing objectives of the DSO. These parameter weights allow this. Normalized weights are calculated as shown in Equation 1 and used as shown in Equation 2.

$$\omega_i = \frac{\lambda_i}{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4} \tag{1}$$

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1 \tag{2}$$

This method is based on the principle of producing a single result by weighting the effects of different criteria using λ weights. Here, ω_i shows the normalized weights.

Following the normalization of the weighting coefficients given in Equation 1 and 2, the input parameters of the dynamic pricing-based energy management model are normalized in order to ensure comparability among variables with different physical units.

The charging station occupancy rate, expressed as $L_s(t)$, represents the percentage utilization of charging station s at iteration t. This parameter is normalized using min–max normalization as:

$$\tilde{L}_s(t) = \frac{L_s(t) - L_{min}(t)}{L_{max}(t) - L_{min}(t) + \varepsilon} \tag{3}$$

where $L_{min}(t)$ and $L_{max}(t)$ represent the minimum and maximum station occupancy rates at iteration t, respectively and ε is a small positive constant introduced to avoid division by zero.

The driving distance between vehicle v and charging station s, expressed as $D_{v,s}(t)$ (km), represents the actual road distance obtained from real-time traffic data. This parameter is normalized using logarithmic scaling as:

$$\widetilde{D}_{v,s}(t) = \frac{log(1 + D_{v,s}(t))}{log(1 + D_{max}(t))} \quad (4)$$

where $D_{max}(t)$ represents the maximum distance value observed at iteration t.

Similarly, the traffic-based travel time v and charging station s, expressed as $T_{v,s}(t)$ $(minutes)$, represents the real-time travel duration under current traffic conditions. This parameter is normalized using logarithmic scaling as:

$$\widetilde{T}_{v,s}(t) = \frac{log(1 + T_{v,s}(t))}{log(1 + T_{max}(t))} \quad (5)$$

where $T_{max}(t)$ represents the maximum travel time observed at iteration t.

The state of charge of vehicle v, expressed as $SoC_v(t)$, represents the current battery level of the vehicle expressed as a percentage. The SoC related priority term is defined as:

$$\tilde{S}_v(t) = \frac{SoC_{max} - SoC_v(t)}{SoC_{max}} \quad (6)$$

where SoC_{max} represents the maximum state of charge value and is set to 100%.

Using the normalized input parameters defined in Equations 3-6 and the normalized weighting coefficients ω_i defined in Equaitons 1 and 2, price score is calculated for each vehicle-station pair as:

$$Score_{v,s}(t) = \omega_1 \tilde{L}_s(t) + \omega_2 \widetilde{D}_{v,s}(t) + \omega_3 \tilde{T}_{v,s}(t) + \omega_4 \tilde{S}_v(t) \quad (7)$$

In order to reflect congestion related price adjustments, an occupancy-based price adjustment factor, expressed as $\phi_s(t)$, is introduced and defined as:

$$\phi_s(t) = \begin{cases} 1.2, & L_s(t) > 90 \\ 0.8, & L_s(t) < 40 \\ 1, & otherwise \end{cases} \quad (8)$$

Finally, the dynamic price value assigned to vehicle v at charging station s is calculated as:

$$p_{v,s}(t) = min(1, max(\varepsilon_p, \phi_s(t) \cdot Score_{v,s}(t)) \quad (9)$$

where ε_p represents a small positive constant ensuring that the resulting price remains in the interval $0 < p_{v,s}(t) \leq 1$.

3. Results and Discussion

In this section, the iterative structure of the developed dynamic pricing-based energy management model and the time-dependent variation of its input parameters are demonstrated. The model was executed for ten iterations, though only selected iterations are presented here as representative examples. These iterations effectively illustrate the typical behavior of the model and the operational mechanism of the price estimation process.

At each iteration, the input parameters are dynamically updated. For instance, in the second iteration, the occupancy rate of Station 3 was 57%, which increased to 64% in the third iteration. This increase was caused by the inclusion of new vehicles in the system and the transition to the charging process. Similarly, in the fourth iteration, the occupancy rate of Station 1 was 72%, but it decreased to 63% in the fifth iteration, indicating that some vehicles completed charging and left the station. Additionally, in the seventh iteration, the traffic duration between Vehicle 1 and Station 3 was 14.6 minutes, which decreased to 10.1 minutes in the eighth iteration. This change demonstrates that the model operates in accordance with the natural flow of urban traffic conditions. Furthermore, the SoC and location parameters also change dynamically with each iteration. These examples demonstrate that the system parameters change consistently and in a physically significant manner with each iteration and that the model's input parameters change dynamically.

The output values (prices) of the model change dynamically at each iteration because the input parameters of the model change dynamically. Table 1 presents the results of the third iteration to illustrate how the dynamic pricing mechanism behaves across different vehicle profiles. The third iteration is presented as a representative example to illustrate the model's operating mechanism. However, consistent and expected pricing behavior is observed across all ten iterations, indicating that the proposed model functions as intended during the simulation. The dynamic pricing-based energy management model produced different prices for 16 vehicles at 4 charging stations due to different input parameters for each vehicle, as shown in Table 1.

Table 1. Dynamic price values.

Vehicles	Station-1	Station-2	Station-3	Station-4
1	0.81847	0.35402	0.83262	0.49114
2	0.80702	0.32253	0.83375	0.44734
3	0.69606	0.17904	0.74583	0.36931
4	0.52061	0.20738	0.73732	0.38899
5	0.74776	0.26865	0.74417	0.34095
6	0.76736	0.31154	0.7794	0.44812
7	0.78503	0.29956	0.7829	0.37308
8	0.61158	0.22301	0.75785	0.39568
9	0.81776	0.32941	0.84225	0.45394
10	0.7442	0.13662	0.74939	0.36893
11	0.67238	0.23524	0.59895	0.38093
12	0.83834	0.3472	0.86313	0.47221
13	0.72092	0.2455	0.79798	0.43455
14	0.72973	0.25547	0.7263	0.3262
15	0.71988	0.24598	0.77744	0.41291
16	0.73109	0.26439	0.73929	0.33956

For the analysis of the model results, Vehicle 1 (with a SoC of 65.13%) and Vehicle 12 (with a SoC of 23.91%) were selected, representing two different charge levels. The purpose of this selection is to comparatively examine how the model adjusts its price estimation under high and low SoC conditions. Both vehicles were evaluated under the same set of charging stations, where the station occupancy rates were 63% (Station 1), 20% (Station 2), 64% (Station 3) and 35% (Station 4), respectively.

Vehicle 1 has a high SoC level (65.13%), which allows the model to evaluate its charging priority in a balanced manner. As shown in Table 1, the price values for this vehicle were calculated as 0.818 (Station 1), 0.354 (Station 2), 0.833 (Station 3) and 0.491 (Station 4). For example, the high price at Station 3 results from its high occupancy rate (64%) and long traffic duration (14.6 minutes). In contrast, the lowest price was observed at Station 2 (0.354), which has the lowest occupancy rate (20%). These findings clearly demonstrate the model's sensitivity to charging station occupancy and traffic parameters.

Vehicle 12 has a low SoC value (23.91%), representing the highest priority charging demand in the system. The calculated prices for this vehicle were 0.838 (Station 1), 0.347 (Station 2), 0.863 (Station 3) and 0.472 (Station 4). The higher price at Station 3 can be attributed to its high occupancy (64%) and long traffic duration (10.9 minutes), emphasizing the dominant influence of λ_1 (station occupancy rate) and λ_3 (traffic) weights in the price function. Conversely, the price decreases to 0.34 at Station 2, which has a low occupancy rate, reflecting the model's tendency to direct users to stations with more available conditions.

Although Vehicle 12's charge level is low, the model appears to assign the lowest price not to the nearest station, but to the station with more favorable traffic and occupancy conditions. This is because the λ_1 (station occupancy rate) parameter in the price function has a higher weight than the λ_4 (weights of SoC) parameter. However, this does not mean that the model only considers grid load. The system assumes the vehicle can reach the station with its current SoC level and performs pricing accordingly. In other words, vehicles with lower SoC are evaluated among the stations within reach and are directed to those with more favorable traffic and occupancy conditions. Thus, vehicles with lower SoC are prioritized but are routed in a way that maintains overall system balance.

Figure 2 presents the dynamic evolution of the price values assigned to a single vehicle at four different charging stations over successive iterations. The results clearly demonstrate that the proposed pricing mechanism produces time varying and station specific price signals rather than static values. While Stations 1 and 3 exhibit relatively higher price levels and moderate fluctuations, Station 2 consistently offers lower prices, demonstrating relatively favorable operating conditions throughout the simulation. In contrast, station number 4 shows significant price variability, reflecting its higher sensitivity to changes in density-related parameters such as occupancy and traffic conditions. Overall, these results confirm that the proposed dynamic pricing-based energy management model is capable of generating adaptive and differentiated price signals in response to evolving system conditions.

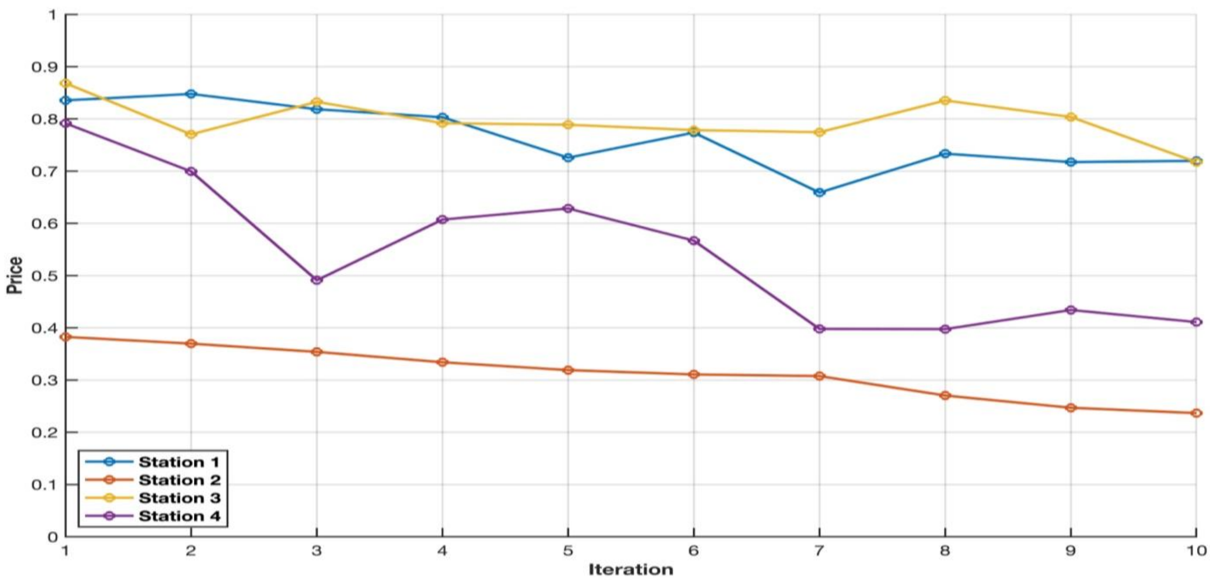

Figure 2. Dynamic prices generated for Vehicle 1 at four different charging stations over ten iterations

The model's dynamic pricing approach considers not only infrastructural factors (traffic, location, occupancy) but also user priorities. This priority is represented by the SoC parameter. Vehicles with low SoC values are considered by the system to be users with urgent charging needs. Therefore, the low SoC-high price relationship is the result of a routing strategy based on user behavior. The goal here is to prioritize the charging needs of low SoC vehicles while preventing this demand from overloading the system. Setting a high price, based on demand separation logic, encourages low SoC vehicles to charge only in truly urgent situations. Low SoC vehicles tend to target the same stations. The price increase also acts as a balancing factor for this congestion.

In the model, some vehicles were included in the system despite having high SoC values. In the real-world, a vehicle with a high SoC value is unlikely to request charging. However, because the aim of this study was to analyze how the model's price estimation mechanism behaves in all possible situations, vehicles were not restricted to a specific SoC range. This allows the system to test both the realistic charging demand behavior of vehicles with low charge levels and the sensitivity of the price function to vehicles with high SoC values. This approach was preferred to observe the consistency of the price variable at different energy levels.

These findings demonstrate that the developed dynamic pricing-based energy management model has a structure that simultaneously evaluates both user behavior and grid load. Within the same city network and station set, differences in vehicle's traffic, station occupancy rate, location and SoC created significant changes in the price. Therefore, the model works both as an economic outcome but also as a dynamic decision support mechanism which balances grid load and affect user demands.

4. Conclusion

A dynamic pricing-based energy management model was developed in this study for EV charging infrastructure. The model is considering four input parameters (traffic, station occupancy rate, location and SoC) which influencing EV charging demand in order to estimate price dynamically. The model was developed in the MATLAB environment and it was supported with real-time traffic data received from the Google Maps API. This makes the simulation dynamic structure reflecting urban conditions.

It was seen from the findings that the developed price prediction model demonstrates beneficial results for both EV users and the DSO. The input parameters and price values were updated dynamically at each iteration. Pricing model was able to balance the grid load while maintaining the charging priority of vehicles with low SoC. The model is reducing system congestion by increasing prices at stations with high occupancy rates and directing users to stations with more available conditions. On the other hand, the decrease was observed in prices at stations with low occupancy rates. This showed that the pricing-based demand balancing mechanism was working successfully on the grid.

The results show that the pricing mechanism produces the lowest prices at charging stations with low occupancy rates. This is because, this input parameter (station occupancy rates) is given the highest weight among all parameters at the input of the model. The pricing model prioritizes both user comfort and the grid balancing objectives of the DSO. However, it was observed that the model produces low prices primarily at stations with low occupancy and to direct EV users to these charging stations unless there are critical SoC levels.

It was seen that the model is sensitive to dynamic urban conditions. The weights employed in the input of the pricing model provide flexibility for the system's behavior different scenarios behavior of system because they defined the relative importance of each parameter. The weights employed in the price function defined the relative importance of each parameter, making the system's behavior flexible to different scenarios. The results clearly demonstrate the potential of such dynamic pricing systems to improve both user experience and energy management, particularly in urban areas.

This model, created in the MATLAB environment, is a basic model designed to test the structure of the dynamic price estimation process. No optimization or artificial intelligence algorithms were used at this stage. The aim of this model is only to observe the relationship between the price variable and the input parameters and the system's dynamic responses.

In future works, the proposed dynamic pricing-based energy management model has the potential to be integrated into power flow platforms, where charging station occupancy indicators can be associated with real-time busbar loading conditions. Moreover, the current heuristic weighting strategy can be strengthened through systematic sensitivity analysis and data-driven tuning of the λ coefficients. Finally, the framework has the potential to be expanded with artificial intelligence and optimization-based approaches to support more adaptive pricing under diverse operational conditions.

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6. Author Contribution Statement

In the conducted work Author 1 contributed to the formation of the idea, literature review, the writing and the development of the model; Author 2 contributed to analysis of the results, the writing and content review; Author 3 contributed to the development of the model, literature review and analysis of the results; Author 4 contributed to formation of the idea, conceptual design of the research and analysis of the results; Author 5 contributed to analysis of the results, the writing and literature review. Author 6 contributed to literature review and the writing.

7. Ethics Committee Approval and Conflict of Interest

"There is no need for an ethics committee approval for the prepared manuscript."
"There is no conflict of interest with any individual or institution in the prepared manuscript."

8. Ethical Statement Regarding the Use of Artificial Intelligence

No artificial intelligence-based tools or applications were used in the preparation of this study. The entire content of the study was produced by the authors in accordance with scientific research methods and academic ethical principles.

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