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Electric Car Price Prediction Using Random Forest Algorithm Comparative Analysis for Türkiye Example and Solution Proposals with Fuzzy Sets

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ABSTRACT

Nowadays, due to the adoption of environmentally friendly technologies and the rising fuel prices, consumers are increasingly turning to electric vehicles. However, it is known that one of the most important factors influencing consumers' decisions to purchase electric vehicles is the sales price. In order for the electric vehicle market to grow globally, it is crucial to implement an effective pricing strategy. In this context, the study estimates the sales prices of 96 electric vehicles of various brands, models, and types across different segments using the Random Forest Algorithm. Additionally, while predicting the sales prices, the model was developed based on 10 criteria commonly used in the literature to evaluate the performance of electric vehicles. The results were used to compare the market sales prices and the predicted sales prices of various electric vehicles as part of a case study conducted in Turkey. Furthermore, the relationship between the market and predicted sales prices was analyzed for the four most important quantitative criteria considered in the literature and by consumers when purchasing electric vehicles. In the final section, solution suggestions based on fuzzy logic were provided for situations involving uncertainty and subjectivity. The study is considered to offer guidance to companies in determining the sales prices of electric vehicles.

1. Introduction

Compared to gasoline- and diesel-powered vehicles, electric vehicles offer significantly greater savings in terms of energy costs. The absence of emission releases, unlike in gasoline and diesel vehicles, also gives electric vehicles an environmentally friendly advantage. In addition, the ease of setting up individual or collective charging stations through infrastructure arrangements and their low maintenance costs have made electric vehicles a preferred choice. From the perspective of driving comfort, the absence of noise during travel and the use of electronic and touch-based components inside the vehicle are among the notable advantages provided by electric vehicles.

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From the driver's point of view, features such as quick acceleration and deceleration, better road grip due to battery placement, and superior cornering performance have been particularly appreciated by those who frequently use vehicles for transportation. In countries like Turkey, special consumption tax reductions provided for electric vehicles further enhance their attractiveness.

Government emission regulations and tax policies, individuals' increasing environmental awareness, changes in energy supply sources, the finite nature of fossil fuels, and technological advancements have all contributed to the growing demand for electric vehicles among consumers.

Especially in the EU countries, the USA, and China, electric vehicle production holds a significant share of the global market. These countries have allocated a large portion of their automobile production to electric vehicles. This suggests that electric vehicle production is expected to increase even more in the coming years. In Figure 1 below, global electric vehicle sales are presented, and in Figure 2, sales forecasts for the upcoming period are shown.

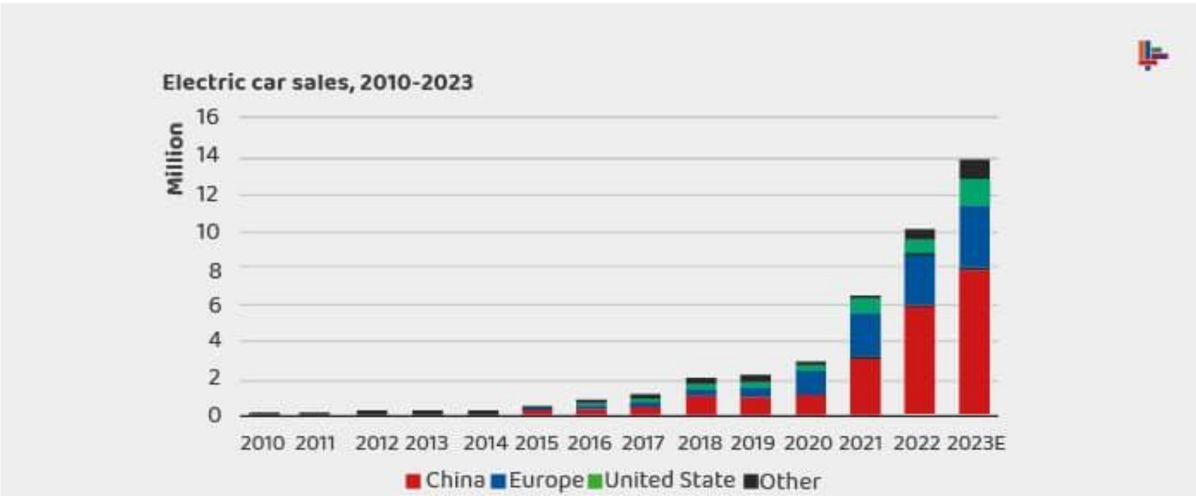

Figure 1: Global Electric Vehicle Sales [1]

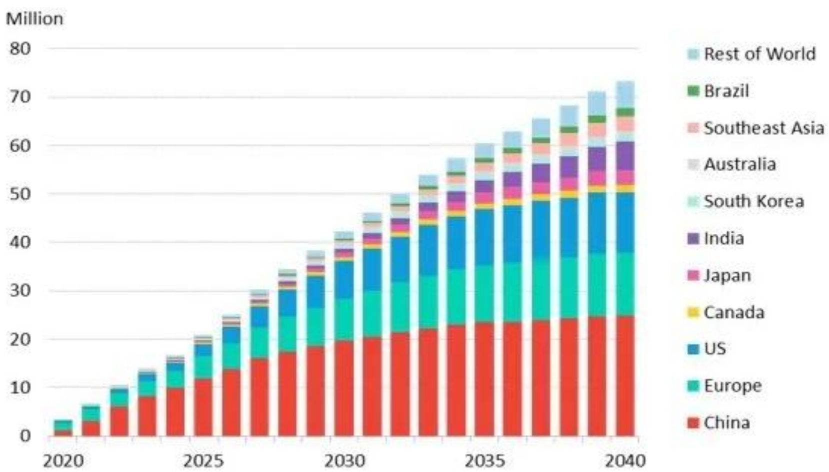

Figure 2: Global Electric Vehicle Sales Forecast [2]

In 2016, the share of electric vehicles entering global traffic was around 1%, whereas by 2020, this rate had increased to 4.6%. According to data from the European Automobile Manufacturers

Association, in the third quarter of 2022, the number of registered electric vehicles across the EU reached 259,449 units (an increase of 22%), marking the strongest growth among vehicle types using different fuel sources.

In Turkey as well, the market share of electric vehicles is steadily increasing. Accordingly, it is anticipated that more consumers in Turkey will prefer to purchase electric vehicles in the near future. This trend has been recognized by TOGG, a domestic automotive brand operating in the country, and on October 29, 2022, the first nationally produced electric car—fully owned in terms of intellectual property rights—was made ready for mass production. It is known that the cost of the vehicle was 750,000 TL as of September 2022, and it was offered for sale at 953,000 TL in March 2023 [3].

According to information provided by the Automotive Distributors and Mobility Association, TOGG was the best-selling electric vehicle in Turkey as of July 2024. The same source states that 1,277 units were sold in July. Between January and July 2024, a total of 14,248 TOGG-brand vehicles were sold. Based on this data, TOGG's market share was reported to be 34.44% [4]. As shown in Figure 3 below, electric vehicle sales in Turkey are on a consistent upward trend [5].

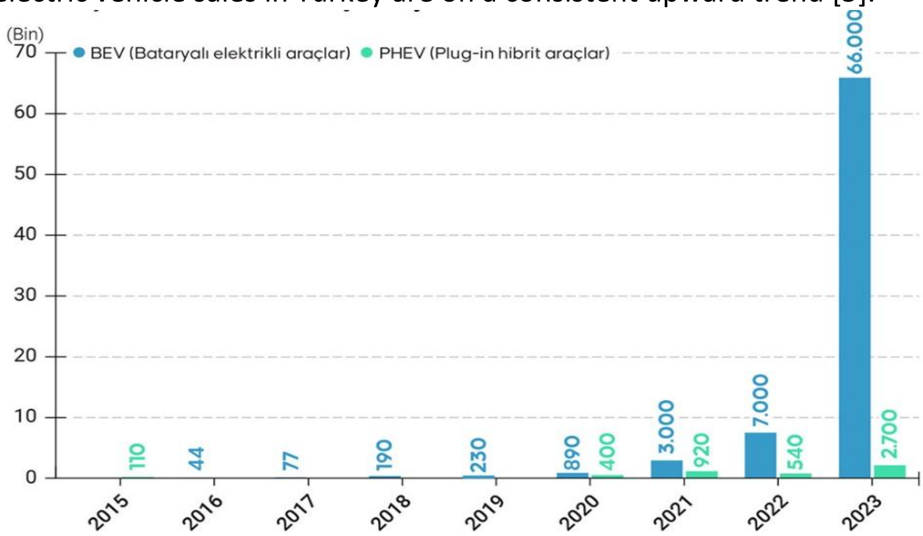

Figure 3: Electric Car Sales in Turkey Between 2015-2023

However, the global increase in the prices of high-tech products has led to higher purchase prices not only for diesel- or gasoline-powered vehicles but also for electric vehicles. Therefore, the pricing policy to be adopted should be designed in a way that does not negatively impact the expected increase in demand.

When making vehicle purchase decisions, consumers try to select the best alternative among various brands and models by evaluating certain criteria. These criteria may include quantitative attributes such as price, fuel type, fuel consumption, engine capacity, horsepower, trunk volume, and sales figures, as well as qualitative attributes such as quality, color, design, and prestige. For this reason, while determining pricing policies, the features of various brand-model-type vehicles and the consumers' price expectations should be taken into account. When making a purchase decision, the consumer will relate the features of other brand-model-type vehicles available in the market to their respective sales prices. Based on this, the final purchase decision will be formed. During this decision-making process, vehicles of different brands, models, and types will be compared by the consumer based on their sales prices. Therefore, such comparisons should also be made by automobile manufacturers when determining their vehicle prices.

In this study, the sales prices for the 2024 period were estimated for 96 electric vehicles of different brands, models, and types, including the TOGG vehicle, using the Random Forest (RF) algorithm. RF is a machine learning algorithm that consists of multiple decision trees and reaches a result by aggregating the outputs of these trees. It is commonly used for solving regression and classification problems. RF was preferred in this study due to its flexibility and ease of use. It allows for building various models using the same dataset and enables in-depth re-analysis of that dataset. RF is recommended for capturing complex nonlinear relationships and is known for having lower computational costs compared to many other popular machine learning algorithms [6,7].

In estimating the appropriate sales price of the TOGG vehicle, the study considered various characteristics of other brand-model-type vehicles. These characteristics were compared to those of the TOGG to predict its ideal price. Accordingly, 10 criteria—identified from the literature as important when evaluating the performance of electric vehicles—were used to estimate the proper sales prices of different brand-model-type electric vehicles. For this purpose, 96 different model-types from 28 different brands available for sale in Turkey were analyzed to estimate the appropriate price of the TOGG vehicle.

The remainder of the study is organized as follows: Section 2 reviews previous research in the literature related to electric vehicle price estimation. Section 3 explains the functioning of the RF algorithm. Section 4 presents the application of the RF algorithm to predict the sales price specifically for TOGG. Section 5 includes fuzzy solution suggestions. Section 6 discusses the results obtained from the study, its limitations, and suggestions for future research.

2. Literature Review

In this study, a variety of perspectives were utilized during the literature review. Artificial intelligence algorithms have been applied in various areas regarding electric vehicles, which is the focus of this study. Given the increasing use of artificial intelligence algorithms as a popular solution tool, the literature was limited to the Random Forest algorithm, which was also the analysis tool for this study.

Upon reviewing the literature, the first studies examined were those related to the RF algorithm and electric vehicles. It was observed that academic studies have increased on topics such as the use of lithium-ion batteries for electric vehicles, the installation of charging stations, and energy consumption [8-11,34]. These studies are critical for developing and optimizing charging infrastructure. Specifically, the strategic placement of charging stations is vital not only to improve users' charging experience but also to enhance the efficiency of energy networks [12]. The studies target sustainable energy solutions and the integration of renewable sources by examining the effects of various charging technologies and methods on energy consumption. Furthermore, they aim to enhance the integration and efficiency of energy systems, such as managing electric vehicle charging processes and the role of smart grids [13,14]. In this way, while reducing the environmental impacts of electric vehicles, the sustainability of energy consumption is also ensured.

Furthermore, in the prediction studies regarding charging stations and energy consumption for electric vehicles, it was found that the RF algorithm is widely used. This algorithm is an ensemble learning method that consists of multiple decision trees and has the ability to model the complexities of datasets effectively [11,15-17]. Predicting the charging demand of electric vehicles requires considering various factors, such as weather conditions, user behaviors, and time slots.

Thanks to its ability to analyze these complex interactions, the RF algorithm provides high-accuracy predictions, aiding in the development of energy management strategies. Additionally, its ability to minimize the risk of overfitting and its resilience to complexities in datasets make it an ideal choice for big data analysis [18]. As a result, the Random Forest algorithm provides a reliable and effective method for prediction studies on electric vehicle charging stations and energy consumption, contributing to the development of sustainable energy solutions.

In recent years, the technological development of electric vehicles and improvements in production processes have reduced the importance of battery and charging issues, while the sales prices of these vehicles have emerged as a more significant economic barrier. First, advancements in battery technologies have increased energy density and reduced costs, thereby largely overcoming the range issues of electric vehicles. Additionally, the expansion of charging infrastructure and the development of fast-charging technologies have alleviated users' concerns about charging times. However, despite these advancements, the sales prices of electric vehicles still remain higher compared to traditional internal combustion engine vehicles, creating a significant barrier for potential buyers. Sales prices, especially for low-income consumers, play a critical role in the adoption of electric vehicles. Putra, Azanuddin, Purba, and Dalimunthe (2023) used Random Forest and decision tree methods to predict car prices [19]. The study predicted sales prices for convertibles, sedans, hatchbacks, hardtop (fixed roof), and wagon vehicles. In the study, sales price predictions were made by collecting generic data from a website. As a result, the RF algorithm achieved an accuracy rate of 72.13%, while the decision tree algorithm achieved an accuracy rate of 67.21%. Furthermore, it was noted that in future research, model-based price predictions would contribute to the literature and decision-makers.

Secondly, studies outside the electric vehicle sector using Random Forest algorithms were also reviewed. Pandey, Rastogi, and Singh (2020) conducted a study on price prediction in the second-hand vehicle market, although not related to electric vehicles. Data for the second-hand vehicle market was collected from various websites [20]. To predict this dataset, two machine learning algorithms—Random Forest and Extra Trees algorithms—were used. The model's predictions were made by comparing it with a test dataset created by selecting random values from the original dataset. As a result, both algorithms were found to be among the best for prediction. Gülmez and Kulluk (2023) similarly conducted a price prediction study for second-hand vehicles[21]. In this study, linear regression, decision tree regression, RF regression, gradient boosted tree (GBT) regression, and isotonic regression algorithms were used for sales price prediction. The study emphasized that the RF algorithm had the highest R2 value. Upon reviewing the literature, it was found that the RF algorithm had been applied successfully in many sectors such as construction [22,23], water [24], cargo [25], and stock markets [26-28]. As a result, it was shown to be a highly effective tool for price predictions, with various advantages such as i) high accuracy ii) reduced risk of overfitting iii) handling missing data iv) fast training and prediction times.

The key feature that distinguishes this study from other works in the literature is the prediction of the TOGG price, its comparison with competitors, and the analysis of the market. While studies using artificial intelligence for price prediction in the literature focus on different car types or second-hand vehicles, none have specifically addressed electric vehicles. Additionally, the success of the RF algorithm in price prediction enhances the reliability of the results in this study.

3. Random Forest Algorithm

Breiman defined the Random Forest (RF) classifier as a collection of tree-based classifiers [29]. In the literature, RF is introduced as an improved version of the bagging method [6]. Tree-based classifiers are treated as independent and identically distributed random vectors. The general structure of the RF algorithm is provided in Figure 4 [30].

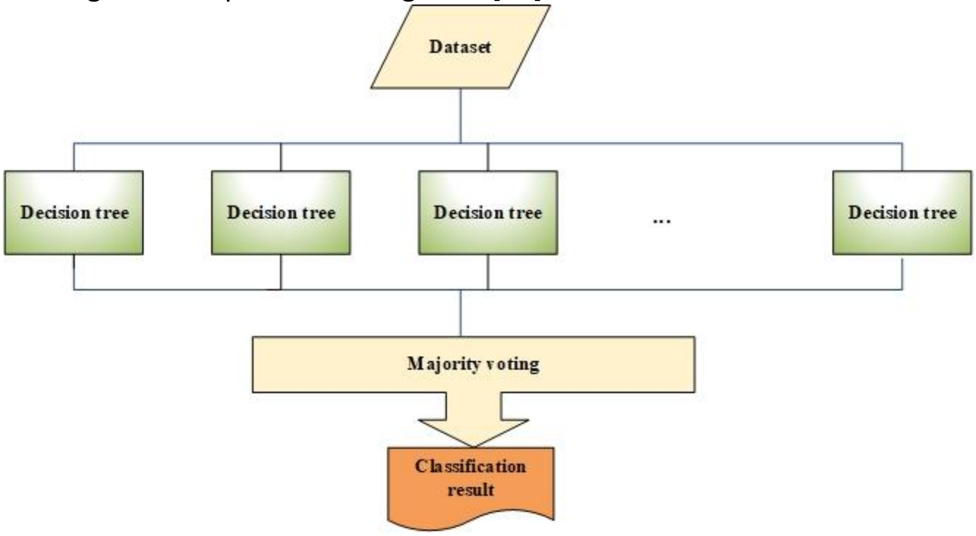

Fig. 4 Random Forest Algorithm

The RF algorithm is a collective learning method that works by generating multiple decision trees during the training phase. In the method, the majority decision from the outputs (trees) is selected by the Random Forest as the final decision [31]. The main advantage of the RF algorithm is that it is a combination of regression and classification. In the RF algorithm, each tree in the forest makes a category prediction, and then, the category that receives the most votes becomes the model's prediction. RF consists of a large number of individual decision trees that work together as a whole [32]. Another excellence of the Random Forest algorithm is its simplicity [20]. In RF, each tree is selected from a random subset of features. This high level of diversity leads to a lower correlation between trees and results in greater diversification. The prominent advantages of the RF algorithm can be listed as follows:

1. There is no overfitting, and it takes less training time.
2. It provides high accuracy and works efficiently with large datasets.
3. It can predict missing values and maintain high accuracy even when there is a large amount of missing data.

4. Applications and Results

Consumers make purchasing decisions by considering various criteria that align with their expectations and needs. One of the most important stages of the decision process is determining the effects of different criteria on the purchase decision, by evaluating the performance levels of various alternatives based on these criteria. When considering the features of electric vehicles, there are different criteria, some of which are related to each other, while others are not. Some criteria are more important to customers, while the effect of others is lower. Therefore, in this study, 10 different subjective and objective criteria that could affect the purchase decision of electric vehicles were determined with the support of literature and sales experts. The values for these criteria were obtained from an open-source electric vehicle database and from catalogs on the official distributor pages of the vehicles [33].

In this study, 96 different models from 28 different vehicle brands are evaluated for 11 alternative electric vehicles based on 10 criteria. Among these electric vehicles, TOGG is also included. Additionally, RF algorithm was used to predict the sales prices of these electric vehicles. Table 1 shows the vehicle brands and their respective quantities considered in the study.

Table 1. Car brands considered in the study

Car Brands			
Tesla (13)	Mercedes (3)	Volvo (1)	DS (1)
Volkswagen (8)	Nissan (8)	Kia (5)	Citroen (1)
Polestar (1)	Hyundai (3)	Renault (5)	Jaguar (1)
BMW (4)	Porsche (5)	Mazda (1)	Ford (4)
Honda (2)	MG (1)	Lexus (1)	Skoda (6)
Fiat (2)	Mini (1)	SEAT (1)	Audi (9)
Peugeot (2)	Opel (3)	Cupra (1)	Smart (3)

In the study, 10 criteria determined with the help of literature and sales experts are as follows: 0-100 acceleration time (sec) (K_1), maximum speed (km/h) (K_2), range (km) (K_3), electricity consumption (efficiency rate) (K_4) (Wh/km), drive type (front-f, rear-r, all-a) (K_5), charging type (K_6), segment (B, C, F, N) (K_8), body type (K_7), number of seats (K_9), and sales price (K_{10}) (Euro). In Table 2 below, the data of some different brand-model-types of vehicles according to the relevant criteria are shown for illustration purposes. The reason these vehicles were selected as examples is that they belong to different segments, are the most demanded vehicles in the market, and have high brand or model recognition.

Table 2. Features of Vehicles Selected as Examples

Car Information											
Brand	**Model**	**K_1**	**K_2**	**K_3**	**K_4**	**K_5**	**K_6**	**K_7**	**K_8**	**K_9**	**K_{10}**
Tesla	Model S Long Range	3.8	250	515	184	AWD	Type 2	Liftback	F	5	79990
Kia	e-Niro 39 kWh	9.8	155	235	167	FWD	Type 2 CCS	SUV	C	5	34400
Skoda	Enyaq iV 50	10	160	290	179	RWD	Type 2 CCS	SUV	C	5	35000
Renault	Zoe ZE50 R135	9.5	140	310	168	FWD	Type 2 CCS	Hatchback	B	5	33133
Honda	e	9.5	145	170	168	RWD	Type 2 CCS	Hatchback	B	4	32997
Kia	e-Soul 39 kWh	9.9	157	230	170	FWD	Type 2 CCS	SUV	B	5	33133
Tesla	Cybertruck Single Motor	7	180	390	256	RWD	Type 2 CCS	Pickup	N	6	45000
Tesla	Model X Long Range	4.6	250	450	211	AWD	Type 2 CCS	SUV	F	7	85990

Peugeot	e-208	8.1	150	275	164	FWD	Type 2 CCS	Hatchback	B	5	29682
Renault	Zoe ZE40 R110	11.4	135	255	161	FWD	Type 2 CCS	Hatchback	B	5	29234
TOGG	T10X	4.8	220	520	169	AWD	Type 2 CCS	SUV	C	5	52035

The values of the vehicles according to the criteria are based on the data from September 2023. Over time, there may be differences in some data due to changes in brand-model-type. After obtaining the values of 96 vehicles based on 9 criteria, the vehicles' sales price prediction was carried out using the RF Regression algorithm, coded in Python. As a result of the analysis, the error value was calculated as 0.052, and the R^2 value was found to be 0.81. Additionally, the estimated sales price of the TOGG brand vehicle based on its features was determined to be 67,245 Euros. According to this, the sales price of approximately 52,035 Euros as of September 2023 is found to be low considering the vehicle's features. In Table 3 below, the actual prices of some vehicles and the predicted sales prices determined using RF regression are shown.

Table-3: Comparison of Market Sales Prices and Estimated Sales Prices of Selected Vehicles as Examples

Model	Real Price (Euro)	Prediction Price (Euro)
Tesla Model S Long Range	79.990	98.140
Kia e-Niro 39 kWh	34.400	33.897
Skoda Enyaq iV 50	35.000	35.251
Renault Zoe ZE50 R135	33.133	31.397
Honda e	32.997	33.291
Kia e-Soul 39 kWh	33.133	34.218
Tesla Cybertruck Single Motor	45.000	60.931
Tesla Model X Long Range	85.990	92.350
Peugeot e-208	29.692	31.107
Renault Zoe ZE40 R110	29.234	29.792
TOGG T10X	**52.035**	**67.245**

When Table 3 is examined, it is observed that for some vehicles, the market sales prices are lower than their predicted sales prices based on their features, for some others, they are higher, and in some cases, the market sales price is very close to the predicted sales price. For the Skoda Enyaq, the predicted sales price is very close to the market sales price. For Tesla vehicles, the predicted sales price for each model type has also come out higher than the current price, similar to the TOGG vehicle. This indicates that, according to the 10 criteria considered, the market price of the vehicles is lower than the predicted price, meaning they are priced lower. On the other hand, the market prices of Kia e-Niro and Renault Zoe vehicles have come out higher than their predicted sales prices. 80% of the 96 different vehicles were used for learning, and the remaining ones were separated for comparison of the prediction with the actual price.

To illustrate the relationship between the predicted sales prices of the vehicles in Table 3 and their features more clearly, the data has been visualized as shown in Figure 4. The 0-100 acceleration time (K_1) and electricity consumption (Wh/km) (K_4) are cost-related criteria, while the maximum range (K_3) and maximum speed (K_2) are utility-related criteria. The quantitative criteria have been normalized using the linear normalization method and converted into utility-type criteria. The main point of the normalization process is to allow the criteria to be evaluated on the same scale, thus eliminating the complexity created by quantitative advantages. Considering the 4 quantitative criteria that electric vehicle users particularly pay attention to, as mentioned in various studies in the literature, the relationship between the market sales prices and predicted sales prices of 11 electric vehicles selected from different segments is shown in Figure 4. The colors used in Figures 4, 5, 6, 7 and 9 are blue acceleration, red red, green range and turquoise efficiency criteria, respectively. In the scatter plots, red represents the estimated price and blue price represents the real price.

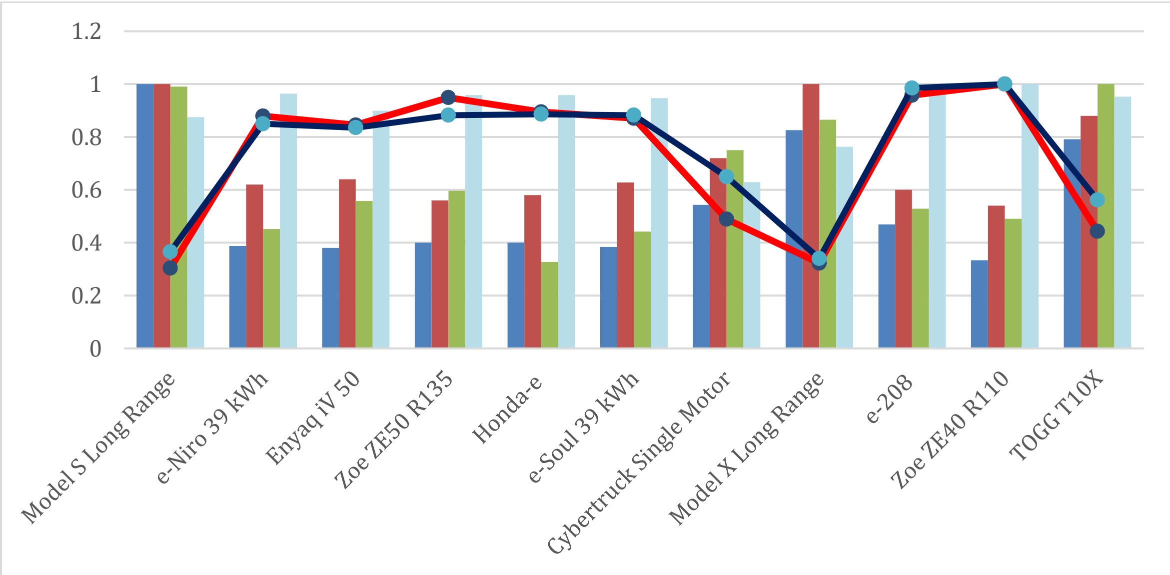

Figure 4: Comparison of Market Selling Price and Estimated Selling Price Based on Quantitative Criteria

When Figure 4 is examined, it can be seen that the Tesla Model-S offers the best price-performance ratio. In this case, the market sales price of the Tesla Model S is the best compared to other brand-model-type vehicles, considering its features. The Tesla Model X follows the Model S in terms of price-performance. In third place, the TOGG T10X emerges as the best option. It is observed that the market sales prices of the other vehicles are higher than expected based on their features. Figure 5 below shows the price-performance comparison of the vehicles, taking into account all the criteria considered in the study.

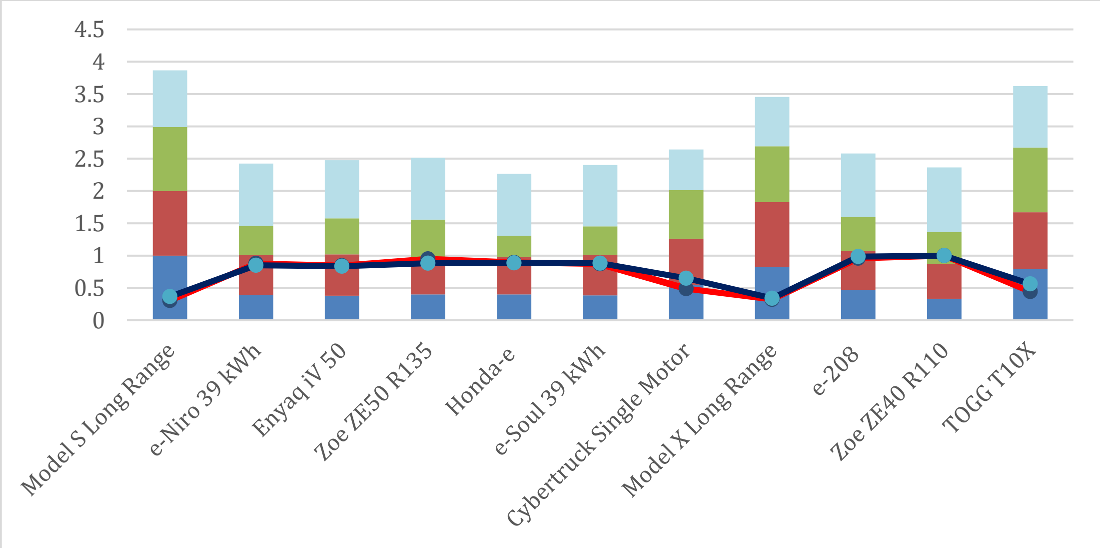

Figure 5: Comparison of Market Selling Price and Estimated Selling Price for Sample Vehicles

As shown in Figure 5, the relationship between the predicted sales prices and the market sales prices is quite consistent. This indicates that determining the price of a new electric vehicle to be introduced to the market using this RF regression method is highly valid. Figure 6 below shows the distribution of the predicted sales prices and market sales prices for several different brand-model-type vehicles.

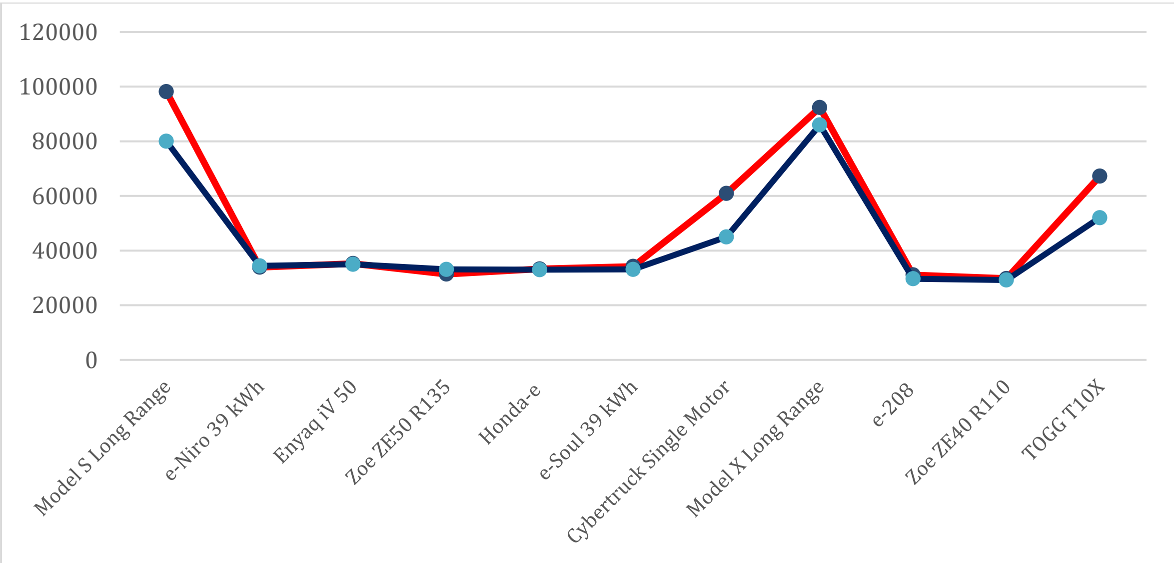

Figure 6: Comparison of Market Selling Price and Estimated Selling Price for Sample Vehicles

As shown in Figure 6, it is observed that for some vehicles, the predicted sales prices are closer to the market prices, while in others, there are deviations. Figure 7 below illustrates the relationship between the vehicles' quantitative criterion values and their market sales prices.

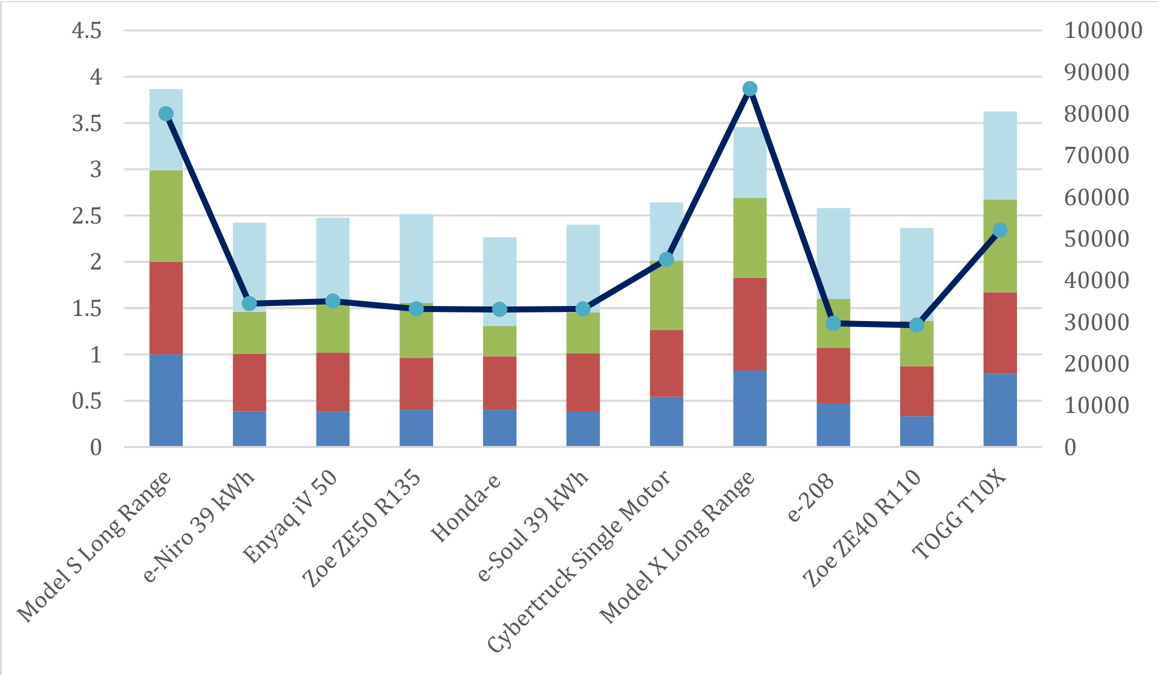

Figure 7: Correlating Market Selling Price with Quantitative Criteria Values for Sample Vehicles

As seen in Figure 7, Tesla vehicles perform well in terms of quantitative criteria, but their sales prices are also high in parallel. When comparing the TOGG vehicle's features with its sales price, it is observed that its price is the lowest relative to its features. Additionally, the price of the Peugeot e-208 model, given its performance, is also found to be lower than expected based on its features.

Another result obtained from the study is the level of impact that the considered criteria have on the market sales price. In Figure 8 below, the strength of the relationship between the criteria is shown by calculating the Pearson Correlation coefficient.

Figure 8: Level of Relationship Between Criteria and Market Selling Price

As seen in Figure 8, the criteria of maximum speed, segment, maximum range, and electric consumption have a positive effect on price, while the brand and number of seats have little effect. Fast charging and acceleration, on the other hand, have a negative impact. In Figure 9 below, the strengths and weaknesses of the 11 selected vehicles, based on the considered criteria, are shown as examples.

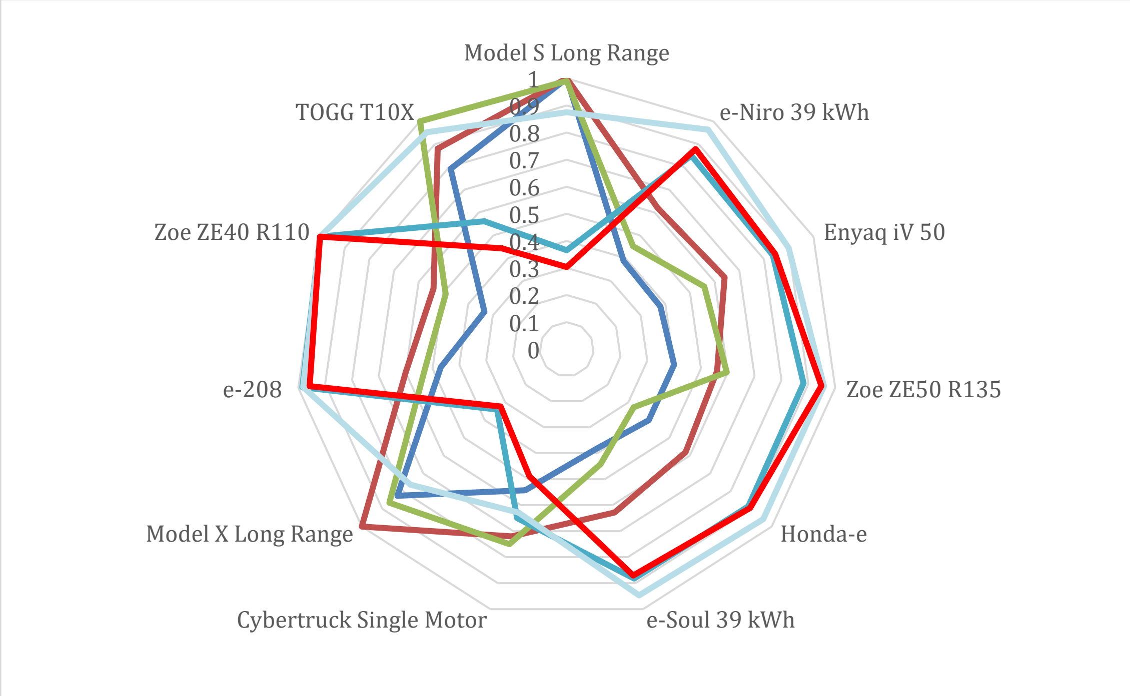

Figure 9: Strengths and weaknesses of sample vehicles according to criteria

As seen in Figure 9, the most important feature of the Tesla Model X Long Range and Tesla Model S Long Range is their maximum speed, while vehicles like the Kia e-Soul, Honda-e, and Renault Zoe have consumption values as their strongest criteria. It is also observed that the predicted sales prices of vehicles like the Peugeot e-208 and Renault Zoe are closest to their market prices. Additionally, it has been determined that the TOGG vehicle excels in features such as maximum range and electric consumption.

5. Fuzzy Logic Solution Suggestions in Electric Vehicle Price Prediction

Accurate prediction of electric vehicle (EV) prices is crucial for guiding consumer choices and supporting strategic planning by manufacturers. However, this pricing process involves not only quantitative data but also subjective judgments, ambiguous boundaries, and numerous interrelated variables. Therefore, when traditional statistical methods and machine learning models prove insufficient, there is a need for artificial intelligence-based approaches that mimic human-like reasoning. In this context, fuzzy logic stands out as an effective method for predicting EV prices due to its flexibility and intuitive structure in modeling complex, nonlinear, and uncertain systems .

Fuzzy logic systems allow for the modeling of real-world concepts by accommodating the inherent vagueness of terms. Variables influencing EV prices, such as range, battery capacity, equipment level, charging time, motor power, and brand perception, are often evaluated using gradual ratings rather than fixed thresholds. For instance, determining whether a vehicle's range is "long" is expressed not by a fixed cutoff value but by a range and a degree of membership. In this framework, each variable is represented by fuzzy sets using linguistic terms like "short," "medium," or "long." For example, battery capacity can be categorized into low (20–45 kWh), medium (40–70 kWh), and high (65–100+ kWh) sets, while range can be categorized into short (100–250 km), medium (200–400 km), and long (350–600+ km) sets. Similarly, the output price can be modeled using fuzzy sets such as low, medium, and high .

A fundamental component of a fuzzy logic-based price prediction system is the rule base defined by expert knowledge. These rules are formulated in an "If...then..." (IF-THEN) structure, specifying how various input combinations correspond to certain price categories. For example, "If battery capacity is high and range is long and equipment level is luxury, then price is very high" is a rule that, when activated by different input values, contributes to the system's prediction. The interaction of these rules enables the system to derive accurate price predictions from complex relationships. For instance, for a vehicle with a 75 kWh battery capacity, 420 km range, mid-level equipment, and high brand perception, the "high" battery capacity and "long" range sets may activate the "very high" price category in the rule base. Subsequently, the fuzzy outputs determined by the system can be defuzzified using methods like the centroid technique to yield a numerical price estimate, such as approximately 1,350,000 TRY. This approach ensures that the model accounts not only for numerical data but also for qualitative judgments and expert knowledge, providing a more reliable and flexible prediction .

In conclusion, the fuzzy logic approach facilitates the development of decision support systems that align with human reasoning in predicting EV prices. Particularly in systems like electric vehicles, where both technical data and expert opinions are crucial, fuzzy logic-based modeling is increasingly preferred in the literature. The rapid changes and uncertainties in the EV market further enhance the effectiveness of such systems, and it is anticipated that these approaches will become more prevalent in the future .

6. Conclusions

Electric vehicles, which have revolutionized the automotive industry, have also become a symbol of sustainable transportation. The increase in environmental awareness, government incentives, and strategic transformations in the automotive sector position electric vehicles as the future of transportation. Over the last decade, the electric vehicle market has gained significant momentum, and it is expected that this momentum will continue to increase in the coming period. Particularly, the reduction in the cost of lithium-ion batteries, government incentives, and innovation-focused policies have led to a year-over-year increase in electric vehicle sales. This is the most significant indicator that the importance of electric vehicles will continue to grow. Rapid advancements in electric vehicle technology have also increased competition. Improvements in battery efficiency, extended range, shorter charging times, and reduced consumption have made electric vehicles more attractive to consumers. These developments have also led to the rapid entry of new-generation entrepreneurs into the industry, in addition to traditional car manufacturers. This, in turn, has led consumers to evaluate vehicle prices and performances in greater detail. The key aspect here is to ensure that the price a consumer pays aligns as closely as possible with the performance they will get, in a cost-effective and efficient manner.

In this study, sales price predictions for 96 different model-types from 28 different vehicle brands on the market were made using RF Regression, considering 9 different criteria. Then, the obtained sales price predictions were compared with the market prices of the vehicles, and it was found that the predictions were 81% accurate. The primary aim here was to predict the market sales price of the TOGG vehicle. According to the results obtained, considering the features of the TOGG vehicle, it was determined that its predicted sales price should be €67,245, while the actual market price was approximately €52,035. This indicates that the market sales price of the vehicle is lower compared to other vehicles with similar features.

Furthermore, it was observed that the brand and seat count criteria had a low effect on the sales price, while criteria such as maximum speed, segment, maximum range, and electricity consumption had a high impact on the price. It was also determined that acceleration time and fast charging criteria were negatively related to the price. Additionally, it was found that the faster the vehicles accelerate, the higher their prices tend to be.

Conflicts of Interest

The authors declare no conflicts of interest.

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