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ELECTRIC CAR COST ANALYSIS AND FORECAST USING A MACHINE LEARNING-BASED METHOD

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Abstract. While there are several environmental and emission-related advantages to electric cars (EVs), the primary factor determining their broad acceptance is their price. It is possible to forecast expenses using ML algorithms. The purpose of this study is to identify the most effective ML algorithm for predicting EV prices by comparing their performance with that of other popular ML algorithms. In order to assess the essential features, we combed through the literature to find out what factors influence the cost of electric cars. To back up our claims, we conducted a theoretical comparison of different ML algorithms and compared the results to what we saw in the simulations.

Machine learning, supervised machine learning algorithm, electric vehicle (EV) prices, and EVs in general are all relevant terms here.

I. INTRODUCTION

Electric vehicles (EVs) provide many advantages in terms of reducing carbon dioxide emissions and the transportation sector's dependency on fossil fuels. Consequently, a number of countries have put in place a range of policies to facilitate the expansion of electric vehicles and reduce strain on their energy infrastructure. Financial incentives, technical support, and charging infrastructure are all things that governments should put in place to promote a broader range of EV use, regardless of the increase in EV use in the last few years [1-2].

A device's or invention's cost is a key consideration. This is related to how widely it has been used by consumers, especially in electric vehicles, which are now fundamental to human survival. Consequently, price is a primary consideration for people when they think about the electric automobile, much more so than other factors like environmental protection and pollution reduction [3-4].

One reason electric cars are so popular is because of their high price. This is due to a number of factors, such as the fact that electric cars (EVs) are not mass-produced at the same rate as traditional ICE vehicles and the fact that the supply chain for EV components—such as batteries, motors, and power electronics—is expanding.

We have read and researched papers on electric car prices based on the latest findings in the field. Consequently, we were able to determine the factors that impact the price of EVs. We used a number of supervised machine-learning methods to conduct

simulations and arrive at an estimate for this cost. We analyzed these results to discover the method that could estimate the price of an EV the most accurately.

The paper's structure is described below: How studies address the topic of electric car prices is covered in Section II. Section III examines the outcomes of the simulations and describes the cost forecast that is based on machine learning methods. As a last step, we review the key points of this study and discuss its future possibilities.

II. COST ANALYSIS OF ELECTRIC VEHICLES

Several studies and publications are now examining the cost of electric cars in an effort to determine the economics of EVs, such as:

With respect to this instance under investigation [6], In order to create a techno-economic model, we used a detailed technical model of both electric and diesel vehicles up to the same section. In order to improve TCO estimates, the project will link complete economic models with accurate and verified vehicle models that use a genuine driving cycle. From 2011 to 2015, total cost of ownership (TCO) for conventional, hybrid, and electric vehicles was examined across fourteen US cities in the present study [7]. The impact of fuel prices, maintenance costs, coverage, and various state and local taxes and levies on cost variability in the largest U.S. cities is highlighted in this research.

By integrating the characteristics of individual EV batteries into a single EV charging model that takes into consideration the connection between the vehicle and the electrical grid, this study [8] offers a framework for optimizing electric vehicle (EV) charging prices and/or emissions with multiple objectives while keeping computational costs to a minimum.

The research study [9] aims to provide a more comprehensive technique for evaluating the entire cost of ownership of electric cars by integrating literature reviews and evaluations. This study adds to the body of knowledge by proving that there isn't a comprehensive method for determining the whole TCO of EVs.

This research [10] uses the most up-to-date information on electric car battery and component prices from 2018 to evaluate the costs of battery electric vehicles from 2020 to 2030. In addition, assessment looks at the predicted time for parity. Typical electric vehicle prices, including sports cars, crossovers, and larger vehicles. For light commercial vehicles in the United States. Electric vehicle-related inquiries In order to determine the best regulatory rules and incentives for making the switch to electric vehicles as the primary mode of transportation, cost parity is usually essential. Several electric propulsion systems are considered in this article [11] as they pertain to the German car industry in 2020 and their cost-effectiveness. To that purpose, this study will provide an in-depth evaluation of the costs associated with various electric propulsion options, with a focus on PHEVs. In this article, we take a close look at the purchase price, ongoing operating expenditures, maintenance costs, and resale prices for various unit configurations of a number of vehicles that are powered to varied degrees by electricity. The total cost of ownership (TCO) of electric light commercial vehicles is affected over time by a multitude of variables. These include the amount of miles traveled, the period of ownership, the residual value of the battery, different tax incentives, and a mileage metering system, among others. This change is discussed in this article [12].

As an example, it shows how conventional vans may benefit from tax breaks and reduced kilometer costs, which might make electric light commercial vehicles more affordable. The total cost of ownership for an electric car may be better understood by looking at how use affects it.

The ownership costs varied by driving style and region, according to this research [13]. This study adds to the body of knowledge by investigating the

geographical variability of OCR at the neighborhood level. In Los Angeles County, four different BEV-ICEV vehicle combinations have had their five-year total cost of ownership (TCO) evaluated: the Nissan Leaf and Versa Note, the Chevrolet Bolt and Trax, the Volkswagen Golf and Golf, the Tesla Model 3, and the Toyota Camry. Discount rate, depreciation, petrol costs, government subsidies, and annual vehicle miles driven (AVM) are just some of the assumptions that their sensitivity analyses explore. Brand, model, acceleration, top speed, range, battery backup, efficiency, quick charging, powertrain, plug type, body design, category, and seats are some of the factors that impact electric car prices, as stated in these articles. We want to use these factors to predict EV prices using supervised machine-learning techniques.

III. ELECTRIC VEHICLE COST PREDICTIONS

When calculating the price of an EV, taking into account specifications, budget constraints, and potential upgrades, it is essential to provide additional data.

Brand, model, acceleration, top speed, range, efficiency, quick charge, powertrain, plug type, body style, segment, and seats are going to be used to forecast the price of an electric vehicle in accordance with electric vehicle certification sites and state-of-the-art technology.

This cost forecast is developed using supervised learning (SLM) methods. Regression prediction makes use of a wide range of supervised learning techniques. Among the most common algorithms, you may find: One of the most popular and easy-to-understand regression approaches is linear regression. The goal and the independent variables are connected in a linear fashion. [20].

- Decision trees: Decision trees are also applicable in regression. By implementing a set of conditional tests, they partition the feature space and use the tree structure to determine the output values [19–21].

- Decision tree-based random forests employ a mix of decision trees to generate predictions. The foundation of each tree is an ad hoc selection of attributes and data points [22].

Support vector machines (SVMs): While SVMs may handle regression tasks, they are more often utilized for classification problems. Using kernel-based algorithms, they seek the optimal distance between the data points. The number 23.

• Models inspired by the way the brain functions are known as artificial neural networks (ANNs). By adjusting the bias and weight of the connections between neurons in their multi-layer architecture, they may be trained to do regression tasks [24].

It is possible to evaluate the performance of several machine learning algorithms and choose the one that is most suited to a given job by taking into account a number of factors. Among the many important factors, we have selected the following:

1. Accuracy: This metric evaluates how well the algorithm can provide precise outcomes. The accuracy rate of a model relative to the total number of examples is called precision in machine learning. The accuracy of a model is 1.0 if it does not generate any false positives. [14]
2. Second, think about the algorithm's learning speed from training data and its execution time while predicting fresh data. Algorithms may vary in how long it takes to learn and how well they function; some may be quicker but less accurate [17].
3. Thirdly, the algorithm's complexity might impact the user's interpretability and comprehension.
4. Learning from a noisy database may lead to the problem of overfitting, which brings us to our fourth point. When a model has too many parameters or is too complicated,

overfitting occurs. The trend in an overfitted model does not represent the actual data, so the model is erroneous. Overfitting may be reduced using a variety of methods, including as regularization, pruning, early stopping, cross-validation, dropout, Bayesian priors, and model comparison [18].

5. Parameterization: Data scientists modify algorithm parameters during setup. Such integers include the algorithm's error tolerance, the number of repetitions, and any variations in its behavior. Parameters may be used to control the algorithm's learning time and accuracy. It usually takes more tries to discover the optimal combination for algorithms with substantial parameters [15].
6. Scalability: When dealing with big datasets, it is essential that the algorithm can manage massive amounts of data. When dealing with massive datasets, some algorithms may outperform others in terms of memory use and execution time. In order to compare and assess supervised machine learning methods, we have chosen to use the star system, which states that the algorithm should be rated as Low (<25%), Medium (<50%), High (<75%), or Very High (<100%).

Table.01 compares supervised machine learning algorithms based on the assessment standards.

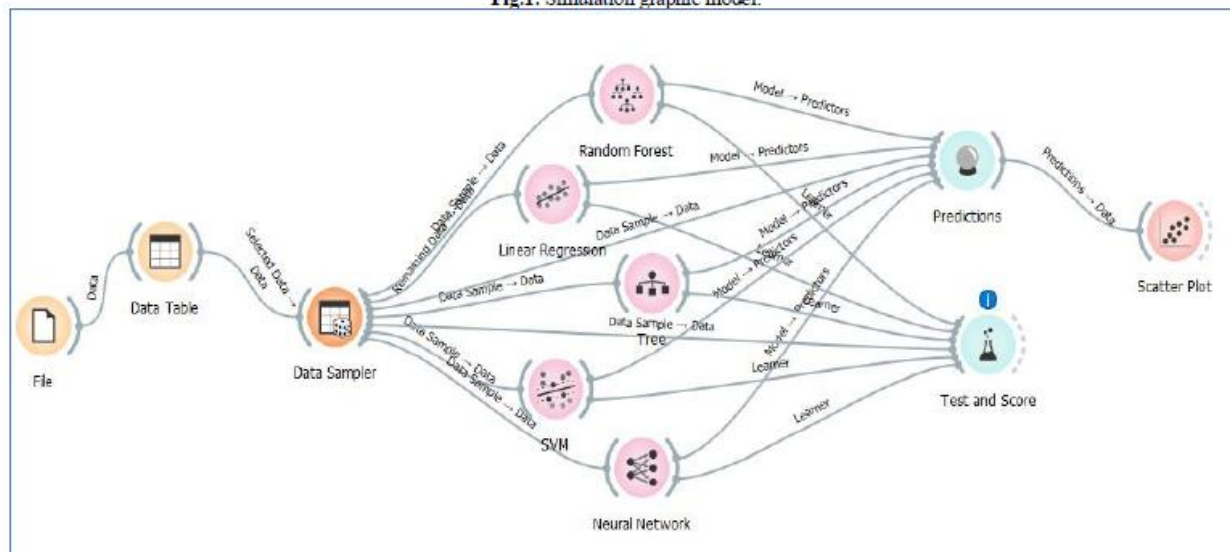
Algo /criteria	Linear regression	Decision trees	Random forests	SVM	ANN
Accuracy	**	**	***	****	***
Learning speed and execution time	***	****	***	**	*
Complexity and interpretability	*	**	***	***	**
Overfitting Tendency	*	***	***	***	**
Parameterization	***	***	***	*	*
Scalability	**	**	***	***	**
Score	12	16	18	16	11

Tab.1. Comparison of algorithms.

Predicting the price of electric vehicles using these algorithms and comparing the results to see how they stack up against state-of-the-art and simulation criteria will validate our comparison according to the criteria we've chosen from the state of the art.

The chosen dataset has fourteen variables and a hundred and forty-four occurrences; it was obtained from the Kaggle website [25]. The goal is to lower the price of EVs. The five machine learning approaches are summarized in Figure 01, which is a visualization graph.

Fig.1. Simulation graphic model.

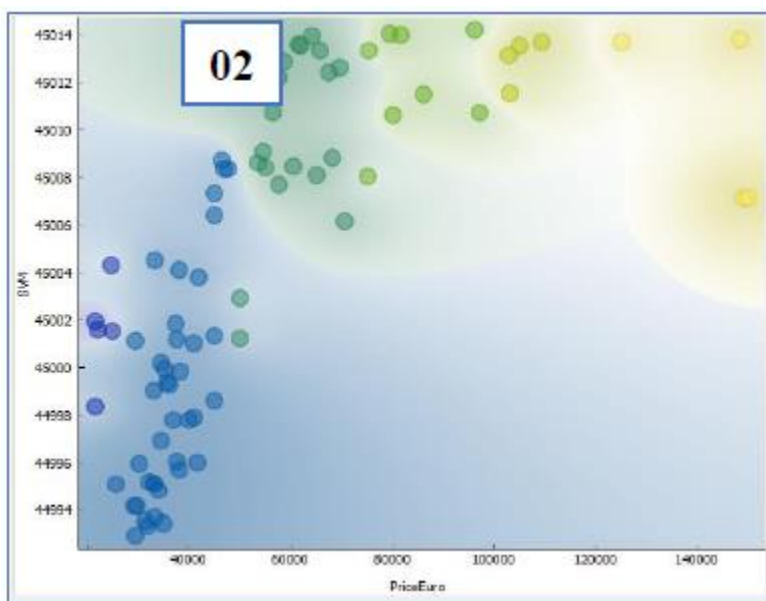
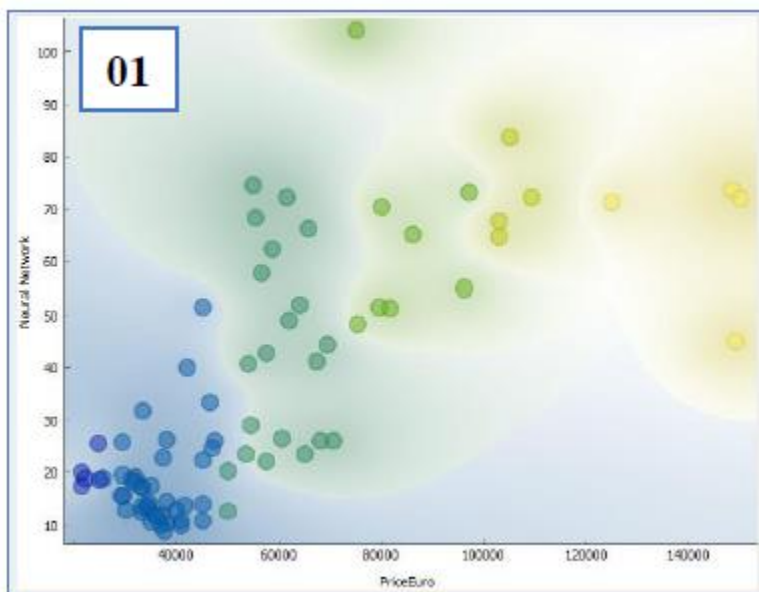


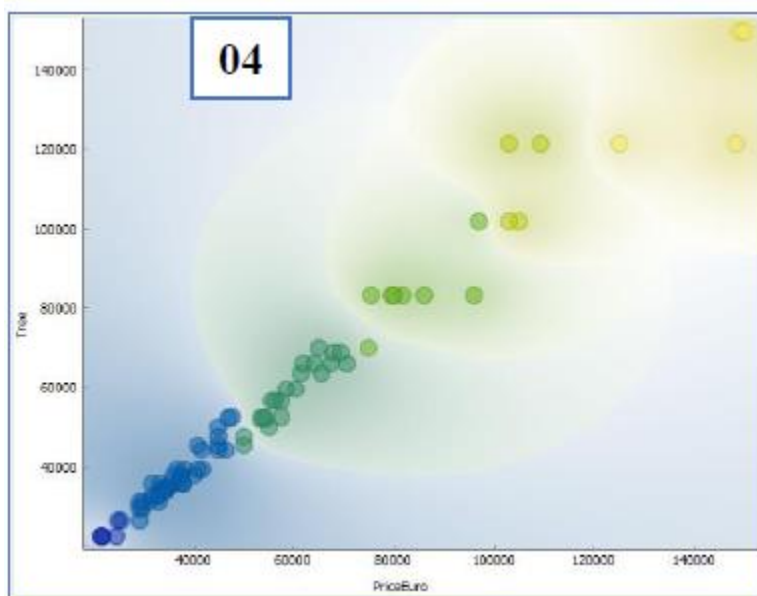
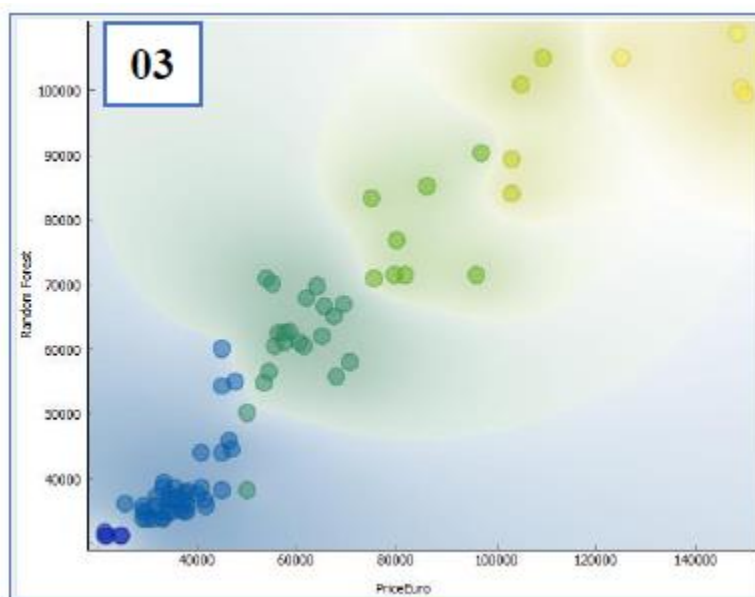
Using the data generated by the algorithms for simulation, we were able to derive the following findings and show how machine learning approaches correlate with electric car prices. in that way:

- **MSE:** Mean square error
- **RMSE:** Root means square error
- **MAE:** Mean absolute error
- **R2:** Coefficient of determination
- **CVRMSE:** Coefficient of variation of RMSE

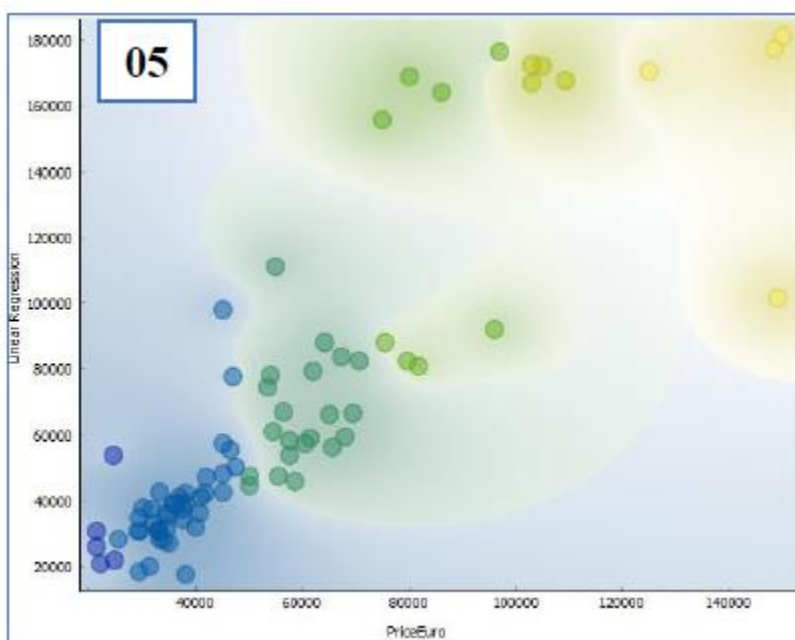
Model	Train time [s]	Test time [s]	MSE	RMSE	MAE	R2	CVRMSE
Linear Regression	0.745	0.416	309342633.629	17588.139	9374.677	0.699	30.668
Neural Network	5.928	0.654	4312377717.417	65668.696	57317.244	-3.194	114.505
Random Forest	1.340	0.452	296724999.574	17225.707	10174.97	0.711	30.036
SVM	1.215	0.594	1139126775.997	33750.952	22742.834	-0.108	58.850
Decision Tree	3.435	0.000	387959716.284	19696.693	11852.672	0.622	34.344

Tab.2. Simulation results.





Figures 01, 02, 03, 04, and 05 represent the variation of algorithms (neural network, SVM, random forest, decision tree, and lean regression) as a function of electric vehicle costs.



IV.DISCUSSION AND CONCLUSION

Table 02 displays the outcomes of the data simulations conducted using five supervised machine learning algorithms: Linear Regression, Support Vector Machines, Artificial Neural Networks, Decision Tree, and Random Forest. In terms of train time, we find that Linear Regression is the quickest method, that SVM and Random forest are almost equal, and that ANN takes the longest. Although the decision tree algorithm's test time is almost nil, the outcomes are same in terms of test time. Nevertheless, the ANN still uses more time than the others. However, all methods change their RMSE and MAE correspondingly; the Linear Regression algorithm has the lowest error, the ANN algorithm has the most error, and the CVRMSE is the same.

Based on these results, we recommend starting with linear regression, moving on to random forest, decision tree, SVM, and lastly ANN as a cost prediction algorithm sequence.

When we compare the simulation results to the state-of-the-art, Conte ranks the Linear Regression approach in the bibliographic section as the fourth best algorithm. This geographical variation happens in relation to the dataset size. Decision trees and random forests both work on very similar concepts. No matter the simulation or the biographic data, the random forest performs similarly.

Inadequate cost prediction capabilities are inherent to the ANN algorithm that forms the basis of the bibliographic research. Keep in mind that as technology improves, manufacturing volumes rise, and the supply chain is streamlined, the prices of electric cars are falling. There is hope that as these factors advance, the cost of electric cars (EVs) will converge with that of gas-powered vehicles.

This research has several limitations due to the tiny datasets used for simulation. It would be beneficial to test the five supervised machine learning algorithms on varying dataset sizes in order to compare their performance and outcomes.

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