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MODELING ELECTRIC VEHICLE ENERGY CONSUMPTION: A SYSTEMATIC AND CRITICAL REVIEW OF PREDICTION METHODS

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ABSTRACT

The dependability and stability of power networks depend on precise predictions of the energy use by electric vehicles. It is becoming increasingly important for utilities to accurately predict when and where demand spikes will occur in order to ensure an adequate supply, especially as the number of electric cars on the road continues to climb.

One major obstacle to reliable demand forecasting for electric cars is the unpredictable and intermittent nature of their power use. Research into creating models capable of efficiently capturing and interpreting such complicated data is, hence, an expanding area of study. A thorough literature analysis, an examination of current research overviews, and the exploration of prospective model extensions and expansions are all key components in boosting the potential of accurate prediction models.

This study provides a thorough summary of previous work on energy demand forecasting for electric vehicles, including an analysis of the methodologies' pros and cons. Furthermore, possible areas where research is lacking are highlighted, and suggestions for future study paths are offered.

I. INTRODUCTION

Warming of the planet during the last many decades is directly attributable to the widespread use of fossil fuels. There should be no more than a two-degree Celsius increase in global temperatures by the end of this century, according to the 2015 Paris Agreement [1]. The transportation industry accounts for more than 25% of the world's total energy consumption, and power generating is one of the most carbon-intensive industries overall [2, 3].

There is a 45 percent decrease in carbon emissions from the use of electric cars compared to traditional vehicles powered by internal combustion engines [4]. The electrification of transport and the transformation of traditional transport systems into smart ones may therefore accomplish the goals of a low-carbon energy future and the reduction of greenhouse gas emissions. Traditional networks and services will also become more efficient with the implementation of smart transport systems and smart cities.

After successfully completing the conceptual process, smart transportation—one of the primary pillars within the smart cities context—has just reached the development stage. To meet the aforementioned pollution regulations and realise the goals of smart cities, conventional transport networks have lately been implemented to enhance car electrification.

Since 2015, there has been a noticeable increase in the number of electric vehicles. The number of electric cars (EVs) on the road has increased dramatically, with the total trebling from 2017 to 2021. The aforementioned rise is seen in Figure 1. This figure is projected to reach 145 million in 2030, up from 16.5 million by the end of 2021 [5]. There will be challenges and possibilities for power systems management brought about by the expected widespread integration of electric vehicles into power systems.

There are environmental and economic advantages to integrating EVs into the power grid,

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but doing so would disrupt the current electric power system in several ways. The most significant negative effects of this deployment are power quality and reliability problems, distribution network bottlenecks, and higher peak load demand [6, 7, 8, 9]. Furthermore, it is possible to significantly reduce carbon emissions using precise EVEC forecasts. By incorporating EVs into the electrical network and optimising charging schedules, the total environmental consequences may be reduced. To accomplish this, less energy is used during off-peak hours and more eco-friendly energy sources are encouraged to be used. Addressing such consequences is crucial for achieving a transportation environment that is more ecologically conscious, from a broader viewpoint.

To that end, power system managers will be better able to control the energy consumption of smart cities with an accurate prediction of EV Energy Consumption (EVEC). In example, a precise prediction of EVEC is necessary for intelligently managing the network of EV charging stations [10]. In addition, it has the potential to improve charging station operations while decreasing maintenance expenses. The results of the EVEC prediction are also crucial for electric vehicle charging infrastructure planning, design, and growth [11]. So, while planning and designing energy systems, it is crucial to take EV energy demand modelling and projection into account.

Electric cars may be a novel idea, but there are already a plethora of studies that attempt to foretell how well they will function. It is difficult to make comparisons since these research use different methodologies. In order to solve this problem, this research classifies the different methodologies used for EVEC modelling and assesses their relative merits in light of the scope of the impact study.

There are a number of review articles on the topic of EVEC prediction, but they all seem to concentrate in on one or two sets of data modelling approaches rather than providing a holistic overview of all the methods accessible across all algorithms. On the other hand, this paper's study gives a thorough overview of the most recent methods for EVEC modelling and prediction. This survey has made the following important contributions:

To give researchers with a good place to start when doing future research on EVEC prediction, the current study synthesises the current literature.

2) The current evaluation evaluates the algorithms employed in previous research investigations, detailing their performance, benefits, and downsides based on a careful examination of the available literature.

Thirdly, it sets the standard by offering a fresh and modern categorisation of the present standard in EVEC prediction, evaluation metrics, and algorithm structure.

4) It finds places where the current literature is lacking and places where more research is needed.

The following is the outline of the paper. There is a rundown of the various EV kinds in Section II. Section III offers a taxonomy of the current methods for predicting EV energy use. The literature on linear models is reviewed in Section IV, while nonlinear and hybrid models are addressed in Sections V and VI, respectively. The criteria for evaluating prediction models are quickly covered in Section VII. Section IX finishes the work and offers suggestions for further research, while Section VIII provides a lengthy discussion.

1.1. Purpose Of The Project

In order to keep current power networks stable and dependable, precise energy demand forecasting for electric vehicles (EVs) is essential. In order to maintain an appropriate and efficient energy supply, utility suppliers must be able to accurately anticipate demand spikes, both in

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terms of time and location, as the adoption of electric vehicles (EVs) throughout transportation networks continues to climb.

But reliable predictions are very difficult to make due to the unpredictable and intermittent character of EV power usage. This has led to a surge in efforts to create sophisticated models that can record and make sense of these ever-changing patterns of use.

The purpose of this study is to summarise the current literature on electric vehicle energy demand forecasts. It contains an analysis of existing methods, pointing out their advantages, disadvantages, and potential uses in different settings. In order to further advance prediction approaches and enable the creation of smarter, more robust energy systems, this study also highlights research gaps and makes suggestions for future work.

1.2. EXISTING SYSTEM

When contrasted with more traditional cars, electric vehicles' (EVs) range is severely lacking. Therefore, there is a great demand for accurate range assessment in electric vehicles in order to eradicate "range anxiety," the panic that drivers have when they worry about their batteries dying mid-trip. But existing electric vehicles' range estimators aren't precise enough. In order to address this problem, researchers are looking at more precise methods of range estimation. Still, getting a good range estimate requires a power-based EV energy consumption model. Modelling the energy consumption of electric vehicles is the subject of this research. To achieve this goal, we simulate electric vehicles (EVs) using the MATLAB/Simulink program, with the market-ready BMW i3 as our basis. Vehicle power train systems and longitudinal vehicle dynamics are part of the electric vehicle model.

Data from the BMW i3's power electronics and electric motor efficiency maps are used to simulate the power train. An comparable circuit model to the one used by Thevenin is also included, along with a model for the gearbox and batteries. To mimic human driving style and regulate the vehicle's speed, a driver model is also created. Furthermore, a regenerative braking strategy is created to mimic the actions of a genuine braking controller, which is based on a series brake system. The EV model incorporates auxiliary devices to enhance the accuracy of energy consumption estimate, as they may significantly affect that. With an error range of 2% to 6% between experimental findings and simulations for EPA and NEDC tests, the vehicle model is tested against published energy consumption numbers, showing a reasonable degree of accuracy.

Disadvantages

- The demand for electric vehicle charging is difficult to predict because of the many unknowns. The unpredictable nature of EV drivers' actions causes these outages.
- Therefore, in order to ensure that electric vehicles are seamlessly integrated into the power grid, it is crucial to include the grid's uncertainties into system modelling and management.

1.3. PROPOSED SYSTEM

1) To give researchers with a good place to start when doing future research on EVEC prediction, the current study synthesises the current literature.

2) The current evaluation evaluates the algorithms employed in previous research investigations, detailing their performance, benefits, and downsides based on a careful examination of the available literature.

3) Thirdly, it sets the standard by offering a fresh and modern categorisation of the present standard in EVEC prediction, evaluation metrics, and algorithm structure.

4) It finds areas that need more research and points out gaps in the current literature..

Advantages

- Nonlinear machine learning methods such as decision trees (DTs) may be used to classification and regression applications.
- K-NN is a technique for machine learning that may function without estimating any

parameters. Classification and regression are two applications of this technique.

- SVR emerged in the 1990s from statistical learning theory and is an expansion of the machine learning method Support Vector Machine (SVM). By fitting the model to the data using a hyperplane that is positioned near to each point, SVR aims to minimise the error obtained.

II. REQUIREMENT AND ANALYSIS

2.1. LITERATURE SURVEY

2.1.1. Overview

"How to fulfil the Paris agreement by 2050—Solar photovoltaic capacity demand for a fully sustainable transport sector,"

E. Rantanen, S. Khalili, D. Bogdanov, C. Breyer, and colleagues

By the middle of the 21st century, all greenhouse gas (GHG) emissions must be zero, according to the Paris Agreement. The transportation industry is expected to achieve zero greenhouse gas emissions primarily via the use of synthetic fuels, including hydrogen and Fischer-Tropsch (FT) fuels, as well as by indirect electrification. This report examines the worldwide need for solar photovoltaics (PV) to meet sustainability goals in the transport industry by 2050. The approach for direct electrification, hydrogen, methane, and FT-fuels is based on the transformation of transportation demand into ultimate energy demand. Assuming a biofuel contribution and an energy transition in the transport sector, the total electricity demand for transport is calculated using the power-to-gas (H2, CH4) and power-to-liquids (FTfuels) value chains. Considering past findings about the proportion of renewable electricity and, by extension, the proportion of solar PV in the power sector's energy transition, this need for electricity serves as the foundation for the demand for solar PV. From 2015 to 2050, the demand for all types of transport, including passenger and freight transit, increased by almost 200%. The relative energy demand is shifting drastically towards the marine and aviation segments, due to the significant direct electrification that is expected in the road and rail segments and the sustained need for liquid fuels in those segments. Approximately 19.2 TWp of total PV capacity will be required by 2050 for the transportation industry worldwide. Of this, 35% will come from direct electrification, 25% from hydrogen, 6% from synthetic natural gas, and 33% from FT-fuels. The FT by-product naphtha, a significant input for the chemical sector and potentially accounting for 14% of the feedstock requirement in 2050, will get an extra 2.4 TWp PV capacity. The transportation industry will be able to fully defossilize with the help of solar PV, which will have a demand similar to that of the power sector but a somewhat later development dynamic. By 2050, the combined annual demand for PV capacity will be roughly 1.8 TWp.

Incentives for electric car adoption on a national level,

J. Xie, X. Zhang, R. Rao, and Y. Liang,

In terms of lowering carbon dioxide emissions and easing transportation's reliance on fossil fuel usage, electric vehicles (EVs) provide clear benefits. Consequently, in an effort to meet environmental goals and reduce energy strain, several nations have implemented laws to encourage the development of electric vehicles and set goals for their implementation in recent years. Even if EV adoption has been on the rise recently, governments could do more to encourage longer EV ranges via policies like financial incentives, technological assistance, or charging infrastructure. We examine potential national policies that may encourage the purchase of electric vehicles in this article. We use the United States as an example to examine the correlation between policy and EV adoption based on this. The article concludes by outlining a few initiatives that have been shown to stimulate the market. As a result, nations should share knowledge and tailor their policies to meet real needs.

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"Analysing the effects of electric vehicle power systems compared to those of vehicles powered by internal combustion engines on global warming,"

Gong, X., Zhang, X., Wang, Z., and Liu, Y.

A potential new strategy to decrease greenhouse gas (GHG) emissions in China is the replacement of electric vehicles (EVs) for traditional gasoline-powered automobiles. The environmental effect on climate change was examined between the power systems of electric vehicles and ICEVs in this research. In order to examine the GHG emissions using IPCC methods, a life cycle analysis model was constructed using the GaBi program. There are four stages to a car's life cycle: producing raw materials, manufacturing and assembling auto components, transporting the vehicle, and finally, using the vehicle. In order to conduct the sensitivity analysis, three different combinations of electric power were considered. With respect to ICEVs as a whole, the GWP was 69.8 percent lower than that of EVs. When looking at the whole vehicle life cycle, however, EVs reduced carbon emissions 45 percent more than ICEVs. Sensitivity analysis revealed that cleaner energy use led to a decrease in GHG emissions. Researchers found that compared to ICEVs, EVs produce less greenhouse gas emissions. The main steps in managing greenhouse gas emissions from electric vehicles were reducing electricity usage during the use, raw materials, and manufacturing stages.

2.1.2 ARCHITECTURE

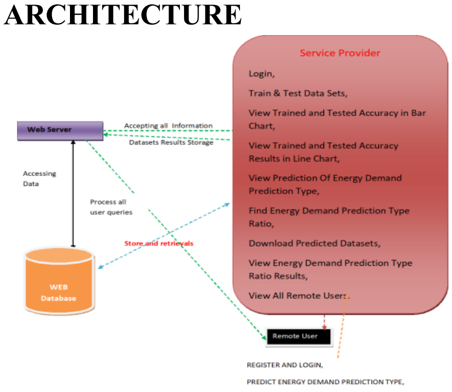

FIG.No.2.1

2.2. MODULES DESCRIPTION

2.2.1. Service Provider

The Service Provider must provide their username and password in order to access this module. Once he successfully logs in, he will have access to many procedures, including Train and Test Data Sets, Check out the Bar Chart for Trained and Tested Accuracy, the Line Chart for Trained and Tested Accuracy Results, see what kind of energy demand predictions are coming out, find out what kind of predictions are coming out of energy demand, and download datasets with predictions already made. See the Outcomes of the Energy Demand Prediction Type Ratio, See All Users From Afar.

2.2.2. View and Authorize Users

The admin can get a complete rundown of all registered users in this section. Admins can see user info like name, email, and address, and they may also grant users permissions.

2.2.3. Remote User

At least n people are active in this module. Do not proceed with any activities until the user has registered. The user's information will be entered into the database after they register. Once his registration is complete, he will need to log in using the credentials that have been authorised. Upon successful login, users will be able to do activities such as registering and logging in, predicting the kind of energy need, and seeing their profile.

2.2.4. ALGORITHIMS

Logistic regression Classifiers

In logistic regression, a group of independent variables is used to study the relationship between a categorical dependent variable and those variables. When the dependant variable may only take on two values—for example, yes or no—the method is known as logistic regression. The situation where the dependent variable might take on three or more distinct values—for example, Married, Single, Divorced, or Widowed—is typically reserved for multinomial logistic regression. While the dependent variable data format differs from

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multiple regression, the procedure's practical application is comparable.

In the realm of categorical-response variable analysis, logistic regression is in direct competition with discriminant analysis. When compared to discriminant analysis, logistic regression is often considered to be more flexible and appropriate for modelling a wider range of scenarios. The reason for this is because, unlike discriminant analysis, logistic regression does not presume that the independent variables have a normal distribution.

For independent variables that are either numerical or categorical, this application calculates logistic regression in two ways: binary and multinomial. Goodness of fit, odds ratios, confidence limits, probability, and deviance are among the metrics reported along with the regression equation. It generates diagnostic residual reports and graphs as part of its thorough residual analysis. It is capable of searching for the optimal regression model using the minimum number of independent variables using an independent variable subset selection search. It offers ROC curves to assist find the optimal classification cutoff and confidence intervals for expected values. By automatically categorising rows that aren't utilised in the analysis, it lets you confirm your findings.

Naïve Bayes

Assuming that the existence or lack of one class characteristic has no bearing on the existence or absence of any other feature, the naive bayes approach takes a basic view of supervised learning and bases its technique on it.

But this apart, it seems to be strong and effective. When compared to other supervised learning methods, its performance is on par. The literature has proposed a number of arguments. We focus on a representation bias explanation in this lesson. Linear classifiers include the naïve bayes classifier, logistic regression, linear support vector machine, and linear discriminant analysis. How the classifier's parameters are estimated (the learning bias) is where the divergence occurs.

Researchers abound with the Naive Bayes classifier, while practitioners looking for practical results are less likely to employ it. Among its many advantages, researchers have noted that it is simple to code and put into practice, has easily estimable parameters, learns quickly even on massive datasets, and outperforms competing methods in terms of accuracy. However, end users do not get a model that is simple to comprehend and implement, and they fail to grasp the value of this approach.

Thus, we provide the learning process outcomes in a novel way. Both the classifier and its deployment have been simplified for better comprehension. Part one of this guide covers the fundamentals of the naive bayes classifier from a theoretical standpoint. We then apply the method to a dataset using Tanagra. Using alternative linear methods like logistic regression, linear discriminant analysis, and linear support vector machines, we compare the outcomes (the model parameters) to our original findings. Notably, there is a great deal of consistency in the outcomes. This is the main reason why the technique outperforms others. Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b, and RapidMiner 4.6.0 are some of the tools used in the second half of the article on the same dataset. Understanding the findings that have been achieved is our primary goal.

Random Forest

An ensemble learning technique for classification, regression, and other problems, random forests (sometimes called random decision forests) work by building a large number of decision trees during training. The majority of trees' chosen class is the result of a random forest when it comes to classification problems. In regression tasks, the average or mean prediction from each tree is given back. If a decision tree tends to overfit its training set, a random decision forest may fix it. To a lesser extent than gradient enhanced trees, random forests perform better than decision trees on average. Their efficiency is, however, susceptible to data quality factors.

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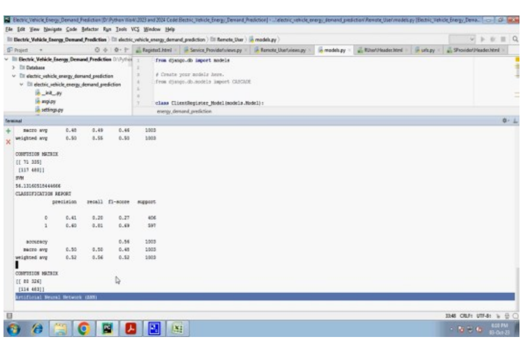
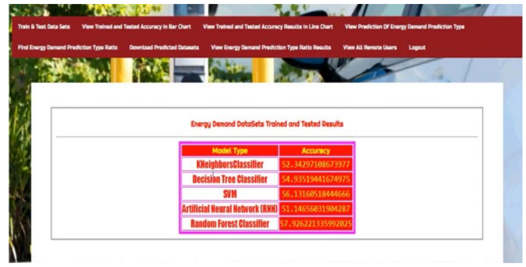
Tin Kam Ho[1] developed the first random decision forest algorithm in 1995 using the random subspace technique. This method is a way to apply Eugene Kleinberg's "stochastic discrimination" approach to classification, according to Ho's description.

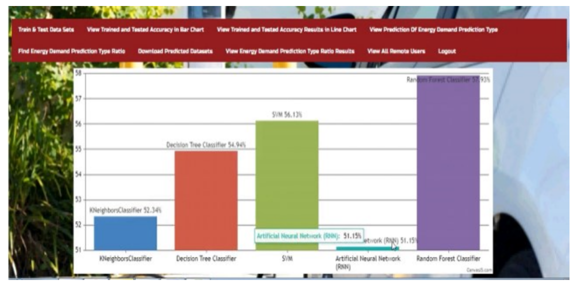
Leo Breiman and Adele Cutler extended the algorithm and in 2006 filed "Random Forests" as a trademark; Minitab, Inc. owns the trademark as of 2019. Constructing a set of decision trees with controlled variance, the extension merges Breiman's "bagging" concept with random feature selection, which was first proposed by Ho[1] and then separately by Amit and Geman [13].

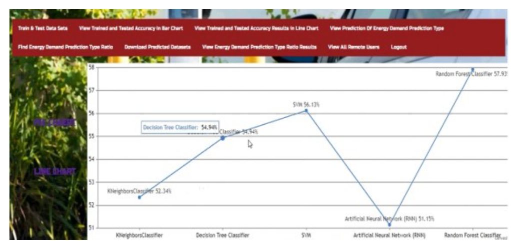
Businesses often use random forests as "blackbox" models because they provide good predictions on a variety of data sets with little setup.

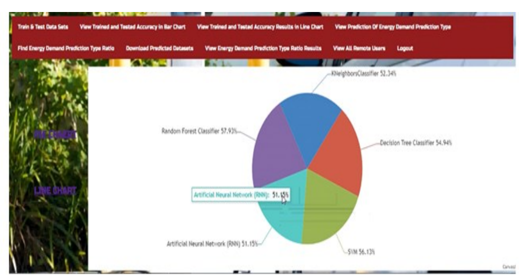
III. SCREEN SHOTS











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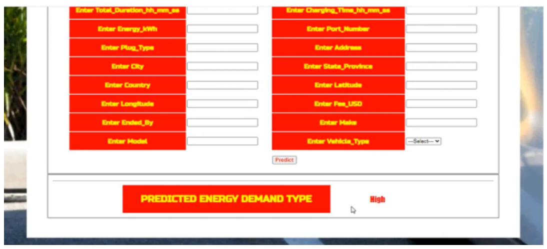

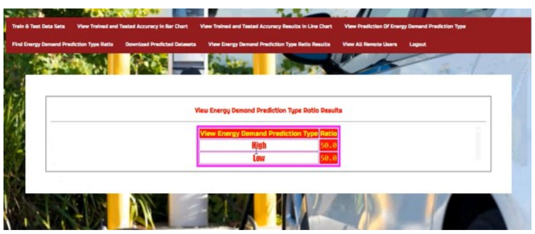

IV. CONCLUSION

This work has reviewed several approaches to energy consumption predictions for electric vehicles, including linear, nonlinear, and hybrid models. All of the methods discussed in this work have their own set of pros and cons when it comes to computational complexity, interpretability, and accuracy. In most cases, the prediction accuracy of models that use a combination of linear and nonlinear methods—hybrid models—was higher than that of other models. Nevertheless, the goals of the prediction job and the specific data characteristics dictate the best model to use. The limitations of these models have been discussed in this work, along with recommendations for further studies.

Technological developments, methodological refinement, and the inclusion of social and environmental factors are all potential areas of focus for future study. Precision and real-time flexibility are both improved by integrating blockchain and IoT applications. Hence, future studies in this area should investigate how to include these technologies. Research into the future should also concentrate on finding ways to improve the prediction models' spatial and temporal precision so that they can accommodate different ways that EVs are charged. In order to get better insights for energy policy and grid management, it is crucial that future research include uncertainty analysis. In addition, experts in this field suggest that researchers conduct EIAs to weigh the environmental effects of various EV energy management systems, such as how they would affect grid load distribution and the possibility of reducing emissions. It should be noted that user psychology is not taken into account in the studied literature. So, to allow customised energy demand forecast models, future research might explore User Behaviour Modelling with an emphasis on understanding the preferences and behaviours of EV consumers. Practical applications also place a premium on Dynamic Pricing Strategies. In order to make the findings more useful, researchers should look at dynamic pricing systems that charge electric vehicles based on grid circumstances, encouraging charging during off-peak hours and strengthening demand response programs.

REFERENCES

[1] C. Breyer, S. Khalili, E. Rantanen, and D. Bogdanov, ''Solar photovoltaic capacity demand for a fully sustainable transport sector—Howto fulfil the Paris agreement by 2050,'' in *Proc. IEEE 7th World Conf. Photovoltaic Energy Convers. (WCPEC), A Joint Conf. 45th IEEE PVSC, 28th PVSEC, 34th EU PVSEC)*, Jun. 2018, pp. 1632–1637.

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https://doi.org/10.62647/ijitce.2025.v13.i2.pp476-485

[2] X. Zhang, J. Xie, R. Rao, and Y. Liang, ‘‘Policy incentives for the adoption of electric vehicles across countries,’’ *Sustainability*, vol. 6,no. 11, pp. 8056–8078, Nov. 2014.

[3] IEA. (2020). *Key World Energy Statistics 2020*. Paris, France: License CC BY 4.0. [Online]. Available: https://www.iea.org/reports/key-worldenergy-statistics-2020

[4] X. Zhang, F. Gao, X. Gong, Z.Wang, and Y. Liu, ‘‘Comparison of climate change impact between power system of electric vehicles and internal combustion engine vehicles,’’ in *Advances in Energy and Environmental Materials*. Singapore: Springer, 2018, pp. 739–747.

[5] IEA. (2022). *Global EV Outlook 2022*. Accessed: Mar. 18, 2023.[Online]. Available: https://www.iea.org/data-and-statistics/dataproduct/ global-ev-outlook-2022

[6] V. Slednev, P. Jochem, and W. Fichtner, ‘‘Impacts of electric vehicles on the European high and extra high voltage power grid,’’ *J. Ind. Ecol.*, vol. 26, no. 3, pp. 824–837, Jun. 2022, doi: 10.1111/jiec.13216.

[7] L. Xiaojun, Z. Xiaodong, Z. Jun, and H. Wenli. (2018). *Energy Consumption and Environmental Impact Analysis of a Novel Vacuum Sewage Collection System: A Case Study in China*. [Online]. Available: https://iopscience.iop.org/article/10.1088/1755-1315/199/5/052033

[8] X. Wu, X. Hu, X. Yin, and S. J. Moura, ‘‘Stochastic optimal energy management of smart home with PEV energy storage,’’ *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 2065–2075, May 2018, doi:10.1109/TSG.2016.2606442.

[9] D. Toquica, P. M. De Oliveira-De Jesus, and A. I. Cadena, ‘‘Power market equilibrium considering an EV storage aggregator exposed to marginal prices—A bilevel optimization approach,’’ *J. Energy Storage*, vol. 28, Apr. 2020, Art. no. 101267, doi: 10.1016/j.est.2020.101267.

[10] H. J. Feng, L. C. Xi, Y. Z. Jun, Y. X. Ling, and H. Jun, ‘‘Review of electric vehicle charging demand forecasting based on multi-source data,’’ in *Proc. IEEE Sustain. Power Energy Conf. (iSPEC)*, Nov. 2020, pp. 139–146.

[11] G. Nalcaci, A. Özmen, and G. W. Weber, ‘‘Long-term load forecasting: Models based on MARS, ANN and LR methods,’’ *Central Eur. J. Oper.Res.*, vol. 27, no. 4, pp. 1033–1049, Dec. 2019.

[12] Z. Chen, R. Xiong, K. Wang, and B. Jiao, ‘‘Optimal energy management strategy of a plug-in hybrid electric vehicle based on a particle swarm optimization algorithm,’’ *Energies*, vol. 8, no. 5, pp. 3661–3678,Apr. 2015.

[13] M. Hannan, ‘‘Hybrid electric vehicles and their challenges,’’ *Renew. Sustain. Energy Rev.*, vol. 29, pp. 135–150, Jan. 2014.

[14] Y. Mu, J. Wu, N. Jenkins, H. Jia, and C. Wang, ‘‘A spatial–temporal model for grid impact analysis of plug-in electric vehicles,’’ *Appl. Energy*, vol. 114, pp. 456–465, Feb. 2014.

[15] B. K. Nelson, ‘‘Time series analysis using autoregressive integrated movingaverage (ARIMA) models,’’ *Academic Emergency Med.*, vol. 5, no. 7,pp. 739–744, Jul. 1998.

[16] M. Pertl, F. Carducci, M. Tabone, M. Marinelli, S. Kiliccote, and E. C. Kara, ‘‘An equivalent time-variant storage model to harness EV flexibility: Forecast and aggregation,’’ *IEEE Trans. Ind. Informat.*,vol. 15, no. 4, pp. 1899–1910, Apr. 2019.

[17] M. H. Amini, A. Kargarian, and O. Karabasoglu, ‘‘ARIMA-based decoupled time series forecasting of electric vehicle charging demand forstochastic power system operation,’’ *Electr. Power Syst. Res.*, vol. 140,pp. 378–390, Nov. 2016.

[18] L. Buzna, P. De Falco, S. Khormali, D. Proto, and M. Straka, ‘‘Electric vehicle load forecasting: A comparison between time series and machine learning approaches,’’ in *Proc. 1st Int. Conf. Energy Transition Medit.Area (SyNERGY MED)*, May 2019, pp. 1–5.

[19] N. Korolko, Z. Sahinoglu, and D. Nikovski, ‘‘Modeling and forecasting self-similar power

International Journal of
Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

https://doi.org/10.62647/ijitce.2025.v13.i2.pp476-485

load due to EV fast chargers,'' *IEEE Trans. Smart Grid*,vol. 7, no. 3, pp. 1620–1629, May 2016.

[20] P. L. Bartlett, P. M. Long, G. Lugosi, and A. Tsigler, ''Benign overfitting in linear regression,'' *Proc. Nat. Acad. Sci. USA*, vol. 117, no. 48,pp. 30063–30070, Dec. 2020.

[21] A. Gerossier, R. Girard, and G. Kariniotakis, ''Modeling and forecasting electric vehicle consumption profiles,'' *Energies*, vol. 12, no. 7, p. 1341, Apr. 2019. [Online]. Available: https://www.mdpi.com/1996-1073/12/7/1341

[22] Y. Xiong, C.-C. Chu, R. Gadh, and B.Wang, ''Distributed optimal vehicle grid integration strategy with user behavior prediction,'' in *Proc. IEEEPower Energy Soc. Gen. Meeting*, Jul. 2017, pp. 1–5.

[23] T. H. C. Tat and P. Fränti, ''Real-time electric vehicle load forecast to meet timely energy dispatch,'' in *Proc. IEEE Int. Conf. Service Oper. Logistics,Informat. (SOLI)*, Jul. 2018, pp. 148–153.

[24] C. De Cauwer, W. Verbeke, T. Coosemans, S. Faid, and J. Van Mierlo, ''A data-driven method for energy consumption prediction and energy efficient routing of electric vehicles in real-world conditions,''*Energies*, vol. 10, no. 5, p. 608, May 2017. [Online]. Available: https://www.mdpi.com/1996-1073/10/5/608

[25] R. Zhang and E. Yao, ''Electric vehicles' energy consumption estimation with real driving condition data,'' *Transp. Res. D, Transp. Environ.*,vol. 41, pp. 177–187, Dec. 2015.