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Time-series Forecasting of Energy Demand in Electric Vehicles and Impact of the COVID-19 Pandemic on Energy Demand

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ABSTRACT

The increase in environmental problems such as climate change and air pollution caused by global warming has risen the popularity of electric vehicles (EVs) used in the smart grid environment. The increasing number of EVs can affect the grid in terms of power loss and voltage bias by changing the existing demand profile. Effective predicting of EV's energy demand ensures reliability and robustness of grid use, as well as aiding investment planning and resource allocation for charging infrastructures. In this study, the electricity demand amounts in Boulder and Perth cities are modeled by Support Vector Regression, Random Forest, Gauss Process, and Multilayer Perceptron algorithms. In addition, the impact of the COVID-19 pandemic on energy demand in electric vehicles and the energy demand behavior of EV owners were analyzed. The findings reveal that electric vehicle owners usually start to charge their vehicles during the daytime, the COVID-19 pandemic causes a severe decrease in EVs energy demand, and the support vector regression (SVR) is more successful in energy demand forecasting. Furthermore, the results indicate that the decline in electricity demand during the COVID-19 pandemic caused reductions in the prediction accuracy of the SVR model (a decrease of 17.1% in training and 12.6% in test performance, P<0.001).

Keywords: Electric vehicles, energy demand, time series, machine learning, COVID-19

1. Introduction

Energy and fuel consumption has a major impact on climate change. The transportation sector ranks second after electricity generation in terms of fossil fuel use [1]. Global warming levels are predicted to be 2°C above if measures are not taken to reduce greenhouse gas emissions [2]. CO2 is one of the most common greenhouse gases, with around 25% of total global CO2 emissions from transportation [3]. The transportation sector is one of the fastest-growing sectors and the automotive sector has sought an alternative energy source due to the effects of greenhouse gases released into the atmosphere. In addition, according to the UK Department of Transport, 97% of energy consumption in transport comes from the use of oil [4]. The amount of use of the currently limited oil reserves is expected to cause the complete depletion of this resource in the near future. These disadvantages necessitate the use of alternative energy sources.

Electric vehicles (EVs) are a reliable alternative to conventional internal combustion engine vehicles as they are more environmentally friendly and energy efficient. Electric vehicles offer lower carbon emissions compared to gasoline-powered vehicles. The popularity of electric vehicles has increased as environmental problems such as climate change caused by global warming and air pollution has become a global problem. Green transportation vehicles such as e-scooter, e-bikes, and bus rapid transit provide significant advantages in terms of energy security, environmental sustainability, combating air pollution, cost savings, and fuel economy [3]. Because of these advantages, many governments and government agencies are developing targets and policies to incentivize electric vehicles. This has further escalated the boom in the EV market in recent years and achieved commercially successful [3]. According to the report of the International Energy Agency (IEA), the number of electric vehicles in the world was approximately 3.1 million in 2017, and it is expected to increase to 125 million by 2030 [5, 6].

The Chinese government offers EV manufacturers many incentives for the commercialization of electric vehicles, such as tax reductions, suspension in the purchase of electric vehicles, and increasing charging opportunities. China has the largest electric vehicle market today. A decade ago, the Chinese government established a medium-term strategy aiming to sell a total of 5 million vehicles by the end of 2020. By the end of 2020, an important milestone was reached with the launch of 4.92 million new energy vehicles, including battery-electric, plug-in hybrid, and fuel cell vehicles [7]. The United States is the second-largest country in the world with EV sales around 30% of the global market. Nationwide sales of plug-in hybrid EVs (PHEVs) and battery powered EVs increased nearly 5x from 2012 to 2018 (increased from 50,000 to 360,000). For many years, California has spent millions of dollars driving EV adoption. It also plans to allocate more funds to future infrastructure work [3, 8]. Energy consumption in the transportation sector in South Korea in 2015 constitutes approximately 18% of the country's energy consumption. About 97% of the country's primary energy consumption is based on imports. The government is promoting the development and use of electric vehicle infrastructure to overcome reliance on oil [3]. In light of the Paris Agreement, it is crucial to continue to promote better modeling techniques for the successful adoption of EVs [9].

The significant increase in the number of electric vehicles shows that the countries efforts to promote green transportation vehicles have been carried out successfully. This increase in the number of vehicles also leads to an increase in electricity demand. The increase in electricity demand may cause an interruption if the balance in the grid is not maintained effectively. An uninterrupted electricity supply is essential for the functioning of modern civilization. Therefore, energy demand/load forecasting plays an important role in the operation and planning of electric power [4].

The machine learning approach is widely used to find solutions to problems such as demand forecasting, power quality, and price forecasting in the smart grid. Ensuring sustainable transportation to meet future energy needs is now a vital mission of the countries. Through computer-aided forecasting methods, electrical power distribution can predict demand and power consumers accordingly.

The main motivation of this study is to propose a robust and highly accurate system that can predict electricity demand through real-world EV consumption values in two different regions. The innovations and contributions brought by the study are as follows.

- To propose an effective machine learning-based approach for energy demand forecasting in EVs,
- To observe the energy demand behavior of EV owners,
- To observe the impact of the COVID-19 pandemic on energy demand in EVs,
- To analyze the impact of the COVID-19 pandemic on the energy demand prediction performance of the machine learning model,
- To contribute to EV charging station planners and operators with a successful energy demand forecast.

2. Related Work

Some studies in this field in the literature, including statistical, machine learning, artificial intelligence, and deep learning in energy estimation in electric vehicles, are summarized in Table 1.

3. Materials and Methods

The use of simulated data or information in modeling studies hinders repeatable work and slows down research in the field. Therefore, it is important to work with real-world data in modeling studies. There is a lot of publicly available real-world data on electric vehicles. Open databases of governments are presented in Table 2.

3.1 Research area and data

In this study, energy demand data for electric vehicles in Perth & Kingdon, and Boulder were used. The reason for using two different real-world datasets is to generalize the success of prediction models. The reason for selecting the Perth dataset is containing many samples and data before the COVID-19 outbreak. The reason for choosing the Boulder dataset is that the number of samples is high, and it contains energy demand samples (COVID-19 data) until the near future. Thus, the effects of COVID-19 curfews on energy demand can be observed, and how forecast models affect forecast performance can be analyzed statistics of Perth and Boulder datasets are given in Table 3. In this study, only the energy demand variable was used since it was estimated based on the time series. This variable includes the energy demand amounts used at different times of the day. However, in this study, the total amount of energy demand per day was calculated and used in learning models. The models were trained with 80% of the datasets, and the prediction performances of the models were tested with 20% of the dataset.

Table 1 Some of the studies in the literature about energy prediction in electric vehicles

Author(s)	**Method(s)**	**Accurate Method**	**Evaluation Criteria(s)**	**Data**	**Performance**
Unterluggauer 2021 [10]	LSTM	LSTM	MAE	demand forecast	$MAE_{shopping}$=4.35 $MAE_{residential}$=1.53 MAE_{public}=2.7 MAE_{work}=1.85
Yi 2021 [3]	Seq2seq, LSTM	Seq2seq	R^2, MAE, RMSE	charging demand	R^2=0.85 MAE=10.6 RMSE=14.73
Na 2020 [11]	LSTM, DBN, LSTM-DBN	LSTM-DBN	MAPE, RMSE	demand forecast	MAPE=1.03 RMSE=5.67
Huber 2020 [12]	QR, MLPs, KDE	MLP	MAPE, MdAPE, Pinball	parking duration, trip distance	Parking duration=13.7% trip distance= 0.56%
Zhang, 2020 [13]	BPNN, SVM, SAE, TDNN, RNN, DBN, CNN	CNN	MAE, MAPE, RMSE	demand forecast	MAPE=3.21
Zhu, 2019 [14]	ANN, RNN, GRU, SAEs, Bi-LSTM, LSTM	LSTM	MAE, RMSE, R^2	demand forecast	MAE=0.29, RMSE=0.44
Zhu, 2019a [15]	DNN, RNN, LSTM, GRU	GRU	NRMSE, NMAE	demand forecast	NRMSE=2.89 NMAE=0.77
Tat 2018 [16]	RNN, LSTM, MLP	LSTM	Accuracy	energy consumption	-
Louie 2017 [17]	SARIMA	SARIMA	BIC, MSE	demand forecast	BIC_{SD}=13150 MSE_{SD}=610.5 BIC_{WA}=13446 MSE_{WA}=808.4
Amini, 2016 [18]	ARIMA	ARIMA	MAE, MAPE,	power consumption	MAE=1.277 MAPE=1.44
Majidpour, 2016 [19]	CNN, CNN+LSTM, T-GCN	T-GCN	RMSE	energy consumption	RMSE=161
Majidpour, 2014 [20]	SVR, RF, kNN, MPSF	MPSF	MAE, SMAPE	energy consumption	MAE=13.05 SMAPE=14.06
Xydas, 2013 [4]	SVM, Monte Carlo	SVM	MAPE, RMSE	demand forecast	MAPE=3.69 RMSE=50.13

MPSF: Modified Pattern-based Sequence Forecasting, SAE: Stacked autoencoder, TDNN: Time-delayed Neural Network, BPNN: Backpropagation Neural Network, RNN: Recurrent Neural Network, DBN: Deep belief network, QR: Quantile regression, MLP: Multi-layer perceptron, KDE: Kernel density estimator, Seq2Seq: Sequence to Sequence, LSTM: Long short-term memory, SeqST-GAN: Seq2Seq Generative Adversarial Nets, SD: San Diego State, WA: Washington State.

Table 2 Electric vehicle charging station datasets by country.

Countries	**Data**	**Reference**
Canada	Historical charging	[21]
Finland	Real-Time charging	[22]
France	Real-Time and Historical charging	[23, 24]
Germany	Real-Time charging	[25]
Netherlands	Real-Time and Historical charging	[26, 27]
Norway	Real-Time charging	[22]
Sweden	Real-Time charging	[22, 28]
UK	Historical charging	[29, 30]
USA	Historical charging	[31-34]

Table 3 Statistics of used datasets in this study

Dataset		Perth	Boulder
Transaction Date	First	09 Jan 2016	01 Jan 2018
	Last	31 Aug 2019	31 Aug 2021
Total Transactions	Weekdays	44664	21198
	Weekends	16393	8022
	All	61057	29220
Park Duration (h)	Mean	1.15	-
	Standard Deviation	2.09	-

3.2 Machine learning models

In this study, different machine learning models are used for energy demand forecasting in Perth and Boulder datasets. These models used are briefly described below.

Support Vector Regression (SVR), is the version of the support vector machine [35] method used for numerical data, that is, for regression. In SVR, there are two situations where the data is linearly separable or linearly inseparable. In linearly separable data structures, two classes can be separated from each other by a line, while to classify data that cannot be separated linearly, the data is moved to a different dimension in various ways, and the data is classified by finding the best separating hyperplane. In nonlinear problems, transformations are performed using kernel functions to analyze the data by moving it to a higher dimensional feature space. The most commonly used are the linear, polynomial, radial basis, and sigmoid kernel functions [36]. Data can be separated linearly by determining the optimum hyper-plane as a result of transformations [37]

Random Forest (RF) [38], consists of two-stage. At the stage of building the RF structure; (i) selection of k features from all features, (ii) compute the node d presenting the best split point among selected features, (iii) create daughter nodes by splitting the node d, (iv) repeat the previous three steps until reaching the desired number of nodes, (v) repeat all the previous steps to build a forest with n number of decision trees. In the estimation stage from the RF model; (i) apply test data to the created decision tree and predict new outputs, (ii) for each predicted value, the votes (importance) are computed, (iii) high voted prediction is considered as the final output value from RF model.

Gauss Process (GP), is a stochastic process in which any finite number of random variables follow a multivariate Gaussian distribution [39]. Various kernel functions are defined on the input samples and the output is created with their weighted sums. The output function is calculated as in Equation (1).

$$\boldsymbol{f(x) = \sum_{j=1}^{H} w_j \Phi_j(x) = w^T \Phi(x)} \tag{1}$$

Here $\Phi(x)$ is a kernel function defined on the input data, w is the weights of the functions, and H is the number of kernel functions.

The process of finding the weights over the predetermined kernel functions is performed with the function minimization optimization in Equation (2).

$$\boldsymbol{J(w) = \frac{1}{2}\sum_{i=1}^{N} (w^T \Phi(x_i) - y_i)^2 + \frac{\lambda}{2} w^T w} \tag{2}$$

Here y_i is the actual value of instance i, λ is the regularization parameter, and N is the number of samples in the training set.

Multilayer Perceptron (MLP), is a fully connected, feedforward type of neural network [40]. MLP consists of at least an input, a hidden, and an output layer. Input neurons transmit the information they receive to neurons in the hidden layer. Hidden layer neurons gather the information they receive from the input layer by weighting, passing it through a function, and transmitting it to the output layer. Output neurons, on the other hand, gather the information they receive from the hidden layer by weighting, passing it through a function, and producing its output. Network training is initially performed by iteratively changing the weights of randomly selected interneuron connections by presenting each training sample to the network. When a training example is given to the network in the training phase, the output of the network is found. Then, for this training example, using the differences between the output of the network and the actual output value, the value of the weights between the neurons is changed to produce values that approximate the actual output. After the outputs of the network are found in the training process, the error value is calculated for each neuron in this layer. After the errors of the neurons in the output layer are found, they are used to calculate the error values of the neurons in the hidden layer. The weights are updated after the error value of all neurons in the network except the input layer is found. This update process for each sample in the training set is called the epoch. The effect of the update process made in the previous step on each update process is expressed with the momentum term.

3.3 Evaluation metrics of models

Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) metrics [41, 42, 43] were used to evaluate the accuracy of machine learning models in forecasting EV electricity demand. Statistical metrics used in this study and their information are presented in Table 4.

Table 4 Performance metrics used in this study.

Metric	**Abbrev.**	**Equation**	**Values**	**Preferred**
Mean Absolute Error	MAE	$\frac{\sum_{i=1}^{n}(y_i - x_i)}{n}$	$[0,+\infty[$	Smaller MAE
Root Mean Square Error	RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$	$[0,+\infty[$	Smaller RMSE
Mean Absolute Percentage Error	MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{x_i - y_i}{x_i}\right\rvert \times 100$	$[0,+\infty[$	Smaller MAPE

n is the number of samples, x_i, y_i : actual and predicted values.

4. Experiments

The total number of vehicles by the time of the Perth and Boulder datasets is given in Figure 1 to observe the charging start time behavior of EV owners. When the graphs are examined, the total number of vehicles that started to be charged between 12:00 and 13:00 for the Perth dataset is the highest. In the Perth dataset, there are 61057 EVs in total, of which 55825, that is, approximately 91.4%, were determined to be starting to charge their vehicles during the daytime (07:00-19:00). When the graph of the Boulder dataset is examined, it is seen that there are three peaks for EVs charge start time. These are the at starting work (08:00-09:00), at lunch (12:00-13:00), and at the end of the working hour (17:00-18:00). It was also observed that approximately 12% of the EVs were charged between 19:00 and 07:00.

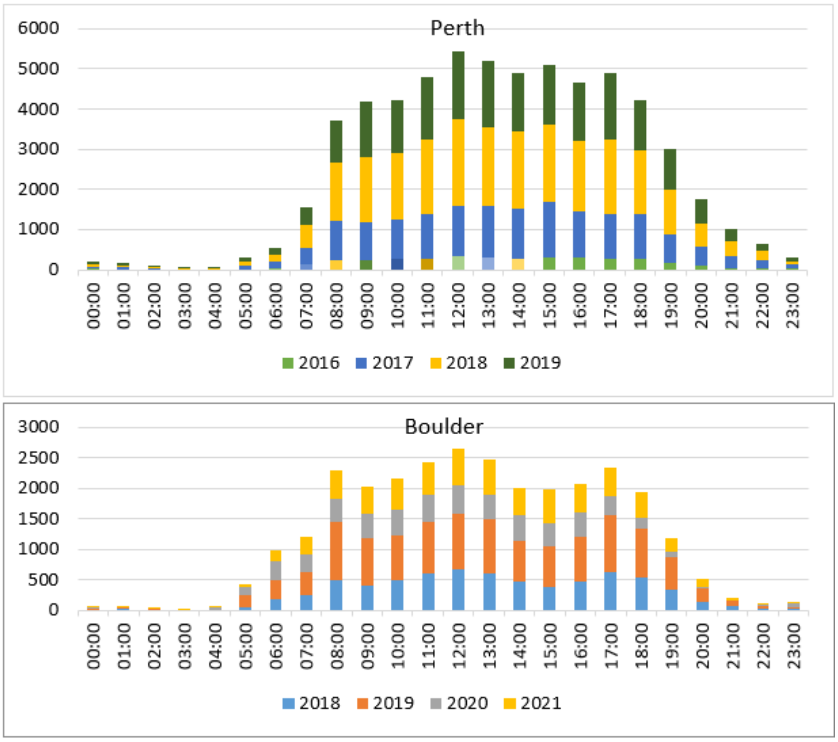

Figure 1 Charging start times of EVs for the Perth and Boulder datasets

The total electricity demand amounts of electric vehicles have been analyzed quarterly and annually, and the graphs are presented in Figure 2.

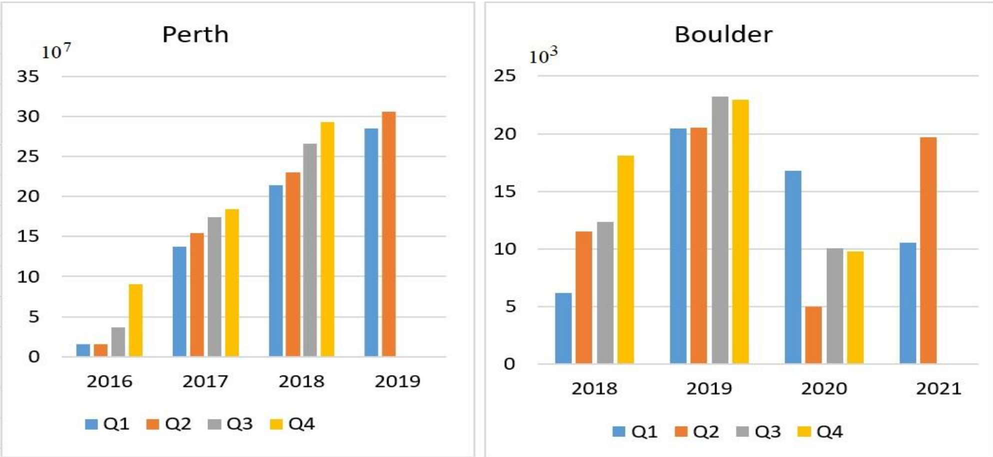

Figure 2 Quarterly total energy demand (kWh) of EVs

The increase in the EV market causes an increase in the amount of electricity demand day by day. When the total energy demand of the Perth dataset is examined, it is seen that the amount of energy demand increases linearly every year. In the Boulder dataset, the total energy demand amount increased considerably in 2019 compared to 2018. However, the COVID-19 epidemic, which started in China in December 2019, caused curfews and thus a decrease in energy demand. The negative impact of the COVID-19 pandemic on energy demand is clearly visible in the 2nd, 3rd, and 4th quarters of 2020 in the Boulder dataset. As a matter of fact, with the relaxation or expiration of the curfews, energy demand increased to its previous levels in the 2nd quarter of 2021. The daily total energy demand amounts in the Perth and Boulder dataset are illustrated in Figure 3. When the daily energy demand amounts are examined, a linear increase is observed in general. However, the curfews due to the COVID-19 outbreak in 2020 caused a significant decrease in the daily energy demand for EVs.

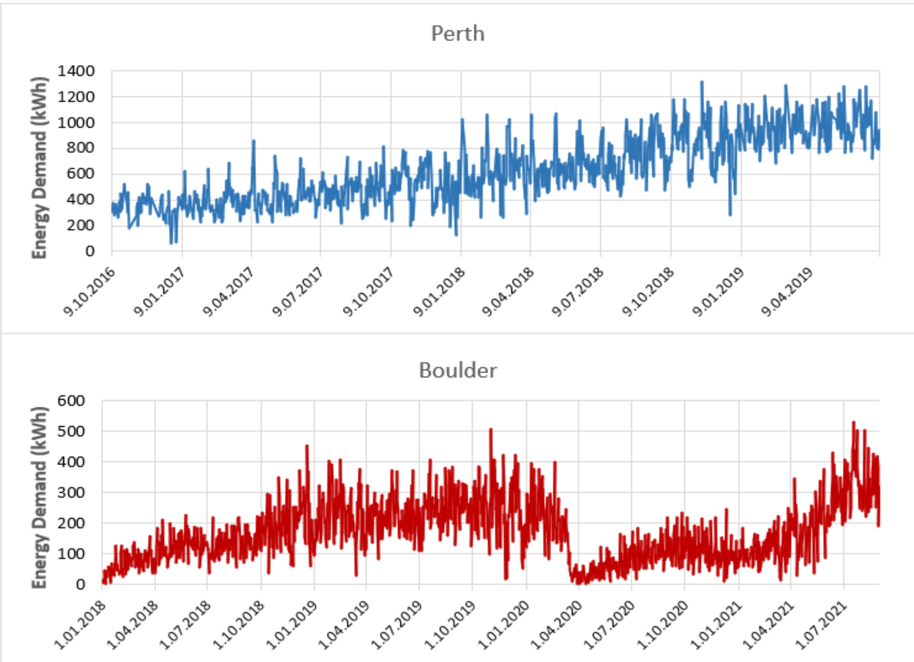

Figure 3 Daily total energy demand (kWh) for the Perth and Boulder datasets

In this study, two different real-world datasets were used to analyze and generalize the energy demand forecasting capability of models. For this, machine learning methods are first trained and then applied to predict at each time point (respectively) by stepping through the data. These forecasts are aggregated and summarized using the MAE (kWh), MAPE (%), and RMSE metrics for each predicted future time step. In this study, 3-time units for forecasting, namely 1-step-ahead (1-s-a), 2-step-ahead (2-s-a), and 3-step-ahead (3-s-a), forecasts are collected and summarized. In this study, each time unit is a day. This allows us to see, to a certain extent, how future predictions change over time relative to closer ones. Models were trained with 80% of the dataset and tested with 20%. Table 5-8 shows the performance of the prediction models on the training and test data for the Perth dataset. Likewise, Table 9-12 shows the energy demand estimation performances for the Boulder dataset.

Table 5 RF model results on the training set (1017 instances) and test set (203 instances) – Perth dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1005	1004	1003	–	203	202	201	–
MAE	40.10	48.35	55.01	47.82	181.51	182.81	187.99	184.10
MAPE	7.50	9.07	10.41	**8.99**	16.75	16.83	17.29	**16.96**
RMSE	51.39	63.61	72.87	62.62	232.87	235.72	242.63	237.07

Table 6 SVR model results on the training set (1017 instances) and test set (203 instances) – Perth dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1005	1004	1003	–	203	202	201	–
MAE	102.35	106.83	107.89	105.69	122.31	120.27	119.82	120.80
MAPE	19.11	20.13	20.37	**19.87**	12.40	12.16	12.10	**12.22**
RMSE	133.03	138.16	140.00	137.06	153.11	150.21	151.95	151.76

Table 7 GP model results on the training set (1017 instances) and test set (203 instances)– Perth dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1005	1004	1003	–	203	202	201	–
MAE	109.26	114.15	114.89	112.77	127.87	132.26	138.31	132.81
MAPE	21.25	22.29	22.38	**21.97**	13.59	14.23	14.97	**14.26**
RMSE	139.01	144.52	146.12	143.22	159.01	165.02	173.48	165.84

Table 8 MLP model results on the training set (1017 instances) and test set (203 instances) – Perth dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1005	1004	1003	–	203	202	201	–
MAE	117.86	139.19	154.19	137.08	381.07	375.82	588.13	448.34
MAPE	19.99	23.21	25.81	**23.00**	37.44	37.78	57.71	**44.31**
RMSE	148.18	173.65	193.62	171.82	514.84	500.78	743.03	586.22

When the energy forecasting performances of the models are compared, it is seen that the SVR method is more successful than other methods for both the Perth and the Boulder datasets. While the estimation methods made more successful estimations for the Perth dataset, it was seen that the estimation error was higher in the Boulder dataset. The higher model error is thought to be due to the sudden decrease in electricity demand caused by the COVID-19 outbreak. For this reason, the energy demand estimation was made again after the period in which the sudden decrease in the Boulder dataset was experienced was removed from the dataset. The dataset was ended in November 2019 so that the performance of the estimation methods would not be affected by the energy drop caused by the COVID-19 outbreak (Figure 4).

Table 9 RF model results on the training set (1068 instances) and test set (267 instances) – Boulder dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1056	1055	1054	–	267	266	265	–
MAE	16.69	20.59	23.63	20.30	74.38	76.93	81.45	77.59
MAPE	18.06	21.81	25.01	**21.63**	48.32	46.79	47.72	**47.61**
RMSE	21.95	27.77	32.58	27.43	100.30	102.47	108.59	103.79

Table 10 SVR model results on the training set (1068 instances) and test set (267 instances) – Boulder dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1056	1055	1054	–	267	266	265	–
MAE	44.02	46.12	46.79	45.64	53.64	57.64	58.70	56.66
MAPE	47.17	49.75	50.31	**49.08**	39.88	38.13	38.19	**38.73**
RMSE	59.20	62.12	63.33	61.55	70.81	76.05	77.61	74.82

Table 11 GP model results on the training set (1068 instances) and test set (267 instances) – Boulder dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1056	1055	1054	–	267	266	265	–
MAE	50.22	53.87	55.09	53.06	68.23	85.25	100.13	84.54
MAPE	66.81	74.37	77.58	**72.92**	46.91	53.56	63.89	**54.79**
RMSE	63.85	68.39	70.36	67.53	83.99	102.42	119.40	101.94

Table 12 MLP model results on the training set (1068 instances) and test set (267 instances) – Boulder dataset

	Training set				**Test set**			
	1-s-a	**2-s-a**	**3-s-a**	**Avg.**	**1-s-a**	**2-s-a**	**3-s-a**	**Avg.**
#instances	1056	1055	1054	–	267	266	265	–
MAE	41.62	46.04	48.99	45.55	364.21	385.87	305.93	352.00
MAPE	35.15	37.68	39.97	**37.60**	200.35	231.60	178.39	**203.45**
RMSE	52.92	58.60	62.53	58.02	470.39	515.60	432.13	472.71

In this study, energy demand estimation was made for Boulder without COVID-19 samples (non-CoV-Boulder) with SVR, which is the most successful estimation method. In Figure 5, the train and test MAPE results of the datasets are presented comparatively. The MAPE metric is the percentage of error. It is seen that the MAPE value decreases for both train and test sets. This shows that the decrease in energy demand negatively affects forecast performance.

5. Discussion

Nowadays green transportation vehicles have been adopted by all governments due to the many advantages they provide, and various incentives are being carried out by State institutions to increase their use. The use of electric vehicles is increasing significantly every year. The increase in the number of electric vehicles brings with it many problems such as insufficient charging stations and the inability to meet the electricity demand. For this reason, many studies have been carried out in the literature on the analysis of the behavior of EV owners and the forecasting of energy demand [44-47].

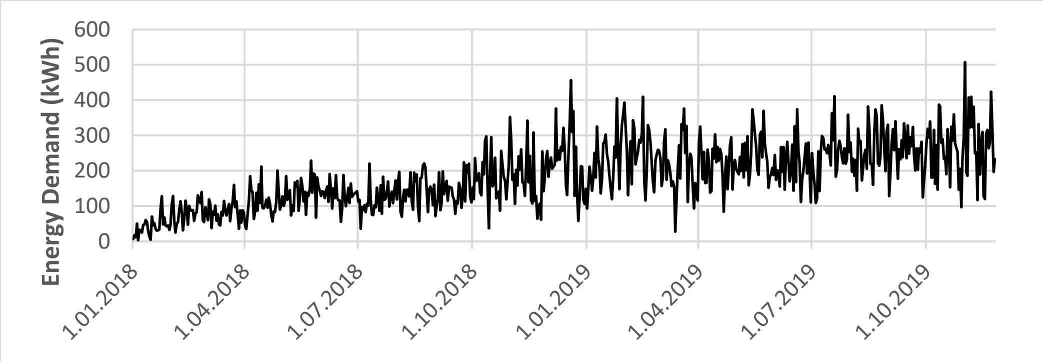

Figure 4 Time series plot of the Boulder dataset without COVID-19 data.

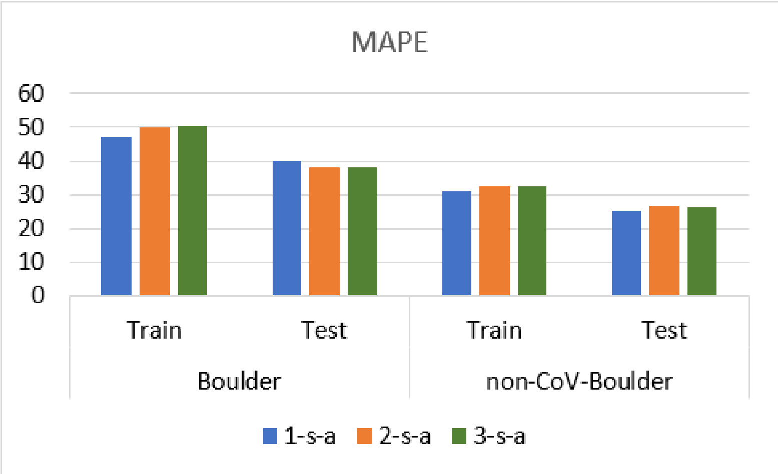

Figure 5 MAPE results of the SVR model for Boulder and n non-CoV-Boulder dataset.

In our study, the total number of vehicles at the start of charging times for two different real-world datasets (Perth and Boulder) was examined to observe the charging behavior of EV owners. In both cities, the starting behavior at night appears to be lower compared to daytime charging (Figure 1). These findings show parallelism with previous studies in the literature [44, 45].

In this study, the most successful forecasting model was determined by comparing the forecasting performances of different machine learning methods for energy demand estimating. Both training and test prediction successes of prediction models are given in detail in Section 4. For a model to be considered successful, the prediction error for the test dataset must be the lowest. The estimation performance of the methods for the test data is summarized in Table 13. The experimental results obtained that the SVR method has the lowest average MAPE value in both test sets.

Table 13 Test average MAE (kWh), MAPE, and RMSE results of all models.

	Perth dataset				Boulder dataset			
	RF	**SVR**	**GP**	**MLP**	**RF**	**SVR**	**GP**	**MLP**
MAE	184.10	**120.80**	132.81	448.34	77.59	**56.66**	84.54	352.00
MAPE	16.96	**12.22**	14.26	44.31	47.61	**38.73**	54.79	203.45
RMSE	237.07	**151.76**	165.84	586.22	103.79	**74.82**	101.94	472.71

In our experience, the reason why the energy demand forecast error in the Boulder dataset is higher than in the Perth dataset is that the Boulder dataset contains the COVID-19 data. Because the drastic decrease in energy demand during curfews (see Fig. 3) reduces the predictive ability of the models. For this reason, the samples in the COVID-19 period were removed from the Boulder dataset, and analyses were performed again. Thus, it was possible to measure the effect of the COVID-19 pandemic on energy demand prediction. The energy demand was predicted with the SVR model, which is the most successful forecasting method, and the MAPE values for 1-s-a, 2-s-a, and 3-s-a are presented in Fig. 6. The Post Hoc test was applied to measure the statistical significance of the mean MAPE values. Experimental results show the COVID-19 pandemic caused a decrease in energy demand for the SVR model of 17.1% in training performance and 12.6% in test performance, P<0.001.

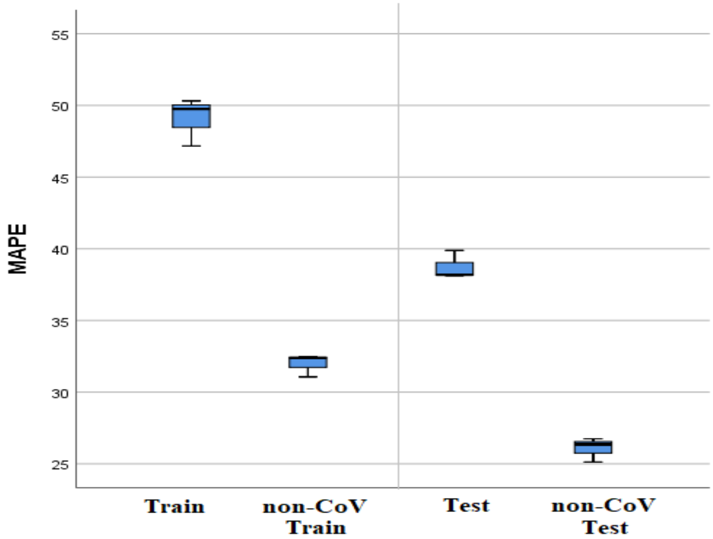

Figure 6 Box-plot of MAPE results

6. Conclusion

Increasing the number of EVs in traffic to reduce global warming and air pollution is among the priority targets of the governments. For this, major incentives are implemented by governments to encourage EV uptake. The serious increase in the number of EVs puts pressure on power system operators. Estimating EV energy demand with good accuracy and reliability is important for the control of the power system. The development of computer-aided energy demand systems will assist in decision-making for electricity market trading. This article contributes to EV energy demand forecasting by comparing machine learning time series models on two different real-world datasets. In addition, the impact of the COVID-19 pandemic on energy demand in electric vehicles and the energy demand behavior of EV owners were analyzed. In the study, the electric vehicle energy consumption of Boulder and Perth city was estimated by SVR, RF, GP and MLP methods. The amount of electric vehicle energy demand in both regions was estimated more successfully by the SVR method ($MAPE_{Perth}$ is 12.2%, and $MAPE_{Boulder}$ is 38.7%). A serious decrease in energy demand has been observed during the COVID-19 pandemic. It was observed that this decrease in energy demand negatively affected the forecast performance of the SVR model. The decrease in demand during the COVID-19 period resulted in a 17.1% decrease in the educational success of the SVR model and a 12.6% decrease in the test pajamas (P<0.001). Finally, it has been observed that electric vehicle owners usually start charging their vehicles during daylight hours.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript.

Availability of Data and Material

Not applicable.

Ethical Approval and Informed Consent

It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

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