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Comparative of prediction algorithms for energy consumption by electric vehicle chargers for demand side management

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ABSTRACT

This study focuses on demand side management (DSM), specifically managing electric vehicle (EV) charging consumption. Power distributors must consider numerous factors, such as the number of EVs, charging station availability, time of day, and EV user behavior, to accurately predict EV charging demand. We utilized machine learning algorithms and statistical modeling to predict the energy required by EV users for a specific charger and compared algorithms like K-Nearest Neighbors, XGBoost, random forest regressor, and ridge regressor. To contribute to the existing literature, which lacks studies on future energy prediction for a specific period, we conducted predictions for the next year 2024 on the energy consumption of electric vehicles for an electric vehicle charging point in a Moroccan city. These predictions can be generalized to other chargers as well. Our results showed that K-nearest neighbors (KNN) outperformed other algorithms in accuracy. This study provides valuable insights for distribution operators to manage energy resources efficiently and contributes to the DSM field by highlighting the effectiveness of KNN in predicting EV charging demand.

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1. INTRODUCTION

In light of the changing climate and the negative effects of air pollution caused by greenhouse gas emissions, researchers are focusing on developing technologies, innovations, and processes that can reduce or eliminate these harmful effects [1], [2]. These research efforts are targeting various sectors, including industrial processes, waste utilization, and value chains. In our specific field, the emphasis is on renewable energy and energy efficiency [3], [4]. It is important to note that road transportation contributes to 23% of total greenhouse gas emissions, making it a significant factor in environmental damage. In Morocco, road transportation generates around 23.23% of total CO^2 emissions, posing a significant threat to the environment and society, particularly due to the high population in urban areas and large cities. To tackle this issue, electric mobility is seen as the most suitable solution [5]. Therefore, Morocco has made a commitment to reduce greenhouse gas (GHG) emissions in the mobility sector and aims to replace 30% of its fleet (equivalent to 35,000 vehicles) with electric and hybrid vehicles (EV/HEV) by 2030 [6]. However, the widespread adoption of EV/HEV vehicles presents challenges for the power grid infrastructure [7]–[9]. To prepare for this upcoming challenge, operators and researchers are actively working on electric vehicle charging infrastructure (EVCI) energy consumption and profiling these patterns using algorithms to effectively manage the expected increase in public charging demand [10], [11]. In the existing works, the majority of research focuses on this topic, but a gap still exists with the absence of future energy predictions.

One of the algorithms used in [12], XGBoost, outperforms other algorithms in terms of reaching the most precise prediction results. In terms of R^2, the model yields a result of 0.519. A mean absolute error (MAE) of 4.57 kWh and a root mean square error (RMSE) of 6.68 kWh. The mean consumption of EV during the session duration is approximately 11.11 kWh. In [12], results reveal that the random forest algorithm has the best validation scores, whereas the other three models (support vector machine (SVM), XGBoost, ensemble methods) have approximately equal metrics (R^2, MAE, RMSE, symmetric mean absolute percentage error (SMAPE)). To form an ensemble model from the previous models, which can combine the performances of the forming models to get an optimal and performant model, the authors selected the three best models, which are random forest (RF), SVM, and XGBoost, to form ensemble models. But unfortunately, the ensemble models did not improve upon the best performing RF model but rather achieved similar results on training. The best results were obtained using the stacking ensemble model. With an R^2 of 0.7, the stacking ensemble model outperforms other models, with an RMSE of 5.5 kWh, MAE of 3.38 kWh, and a SMAPE of 11.6%. Energy consumption prediction by the voting ensemble gives results almost as important as the stacking ensemble, and the resulting scores are approximately similar, with an R^2 of 0.69, RMSE of 5.54 kWh, MAE of 3.41 kWh, and a SMAPE of 11.8%. In another study focusing on Morocco, the researchers in [13] applied a deep learning approach to predict the duration of charging sessions. They utilized algorithms such as recurrent neural network (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU), and assessed their effectiveness using metrics like mean squared error (MSE), RMSE, and MAE. The papers [14]–[16] reveals that lower scores in these metrics indicate more accurate predictions, suggesting that the predicted data closely approximates the actual values. The results indicated that the RNN algorithm yielded higher values of MSE, RMSE, and MAE, suggesting a significant discrepancy between the predicted and actual charging session durations, thereby making it less effective compared to the other algorithms. For the LSTM algorithm, an MSE of 1.523%, which is only 20% of the MSE for RNN, indicates that its predictions of session duration are much closer to the actual charging durations. Overall, the results demonstrate that the gated recurrent unit (GRU) model surpasses both RNN and LSTM in performance.

In this study, we initially introduced the artificial intelligence algorithms utilized for predicting EV energy consumption. We provided a concise definition along with supplementary information about how these algorithms function (KNN, XGBoost, random forest regressor, and ridge regressor). Following that, we discussed the metrics employed to evaluate the performance of these algorithms, which are MAE, MSE, mean absolute percentage error (MAPE), and execution time. Lastly, we presented the outcomes using visual representations. To accomplish this, researchers are advised to begin by reviewing existing papers treating algorithms employed for EV charging prediction and identifying any gaps in current knowledge. The aim of this work is to make a comparison between AI prediction algorithms with the concept of predicting future energy consumption by giving the algorithm a list of future dates.

This paper is organized into several sections. Section 1 serves as the introduction, setting the stage for the research presented. Section 2 details the methodology, emphasizing data content, cleaning operations, and the criteria for selecting data for both training and testing. This section also introduces the AI algorithm utilized in the study. Section 3 presents the results derived from the algorithm, showcasing numerical data and figures that illustrate these findings. The paper concludes in section 4 with a summary of the research and offers perspectives on future work.

2. METHOD

The dataset used to train the models for predicting EV charging energy requirements contains information about the charging patterns of electric vehicles. It is important to note that this data is related to an energy distribution network, indicating that it is derived from a group of EV charging stations that receive electrical power from the same supplier. The dataset is a 5-year energy consumption record of an electric vehicle charger in Rabat city in Morocco. The load curve in Figure 1 illustrates the consumed energy over 5 years in kWh. In Figure 2, we have depicted the training dataset and the test dataset using a single curve. This selection of training and testing datasets was made after conducting an analysis of multiple iterations to determine the optimal performance. This visualization technique allows us to assess the effectiveness of the selected datasets and make informed decisions regarding their usage in the model training and testing processes.

The methodology initially concerns the data collection to form the foundation of the analysis. This collected information then needs processing, where it is cleaned and prepared for examination. The next step involves exploratory data analysis, during which the prepared data is thoroughly examined to uncover patterns, trends, and valuable insights. These initial stages are crucial as they lay the groundwork for the subsequent modeling and forecasting activities, ensuring a robust and accurate prediction of energy consumption and revenue forecasts [17].

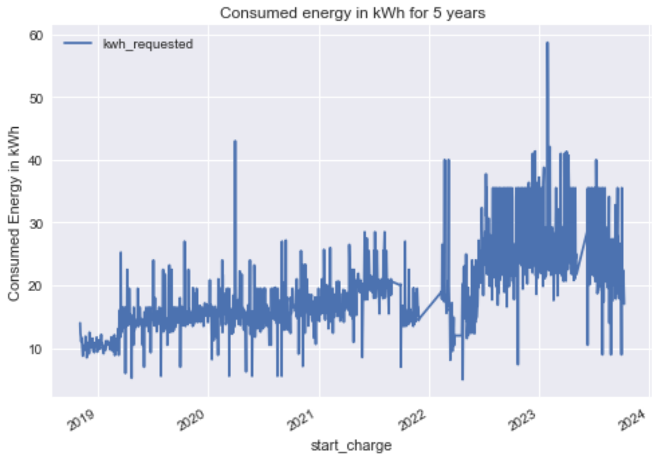

Figure 1. Requested energy for 5 years from the dataset

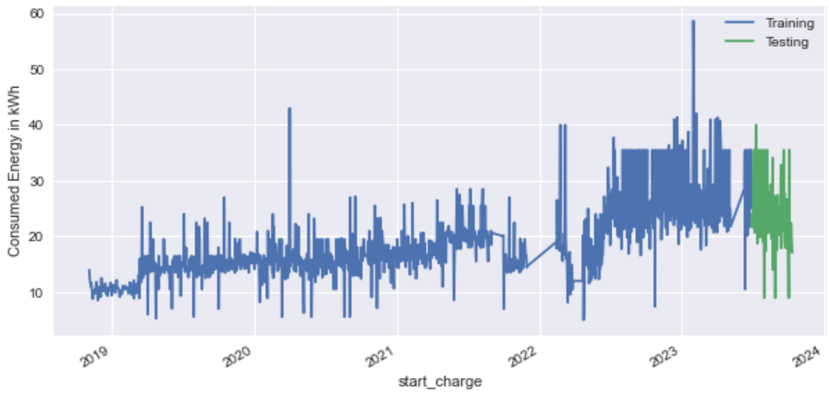

Figure 2. Training and testing dataset

The data used for this purpose was strategically divided, with 80% allocated for training the models and the remaining 20% used for testing their accuracy. This specific split was finalized after several iterations to determine the most effective distribution for optimal predictive performance. The chosen ratio of 80% training to 20% testing consistently produced the best outcomes, striking a balance between learning complexity and validation effectiveness.

2.1. Random forest regressor

Random forest regressor is a popular ensemble machine learning algorithm commonly used for tasks including classification and regression. It works by creating multiple decision trees during the training phase. This algorithm aggregates a collection of decision trees to perform classification and regression operations, making it capable of making accurate predictions [18].

2.2. XG-Boost

Gradient boosting is an effective supervised learning technique that aims to make precise predictions of a target variable. It achieves this by aggregating the predictions of several weak models. This algorithm is particularly advantageous when dealing with datasets of medium size. XGBoost shows good results in terms of speed, accuracy, and efficiency [19]. There are several variations of the gradient boosting algorithm, including XGBoost, LightGBM, and CatBoost.

2.3. KNN

The KNN algorithm is a type of instance-based learning method used in machine learning for classification and regression tasks [20]. It operates on the premise that similar data points are close to each other. The algorithm calculates the distance between a query example and every example in the dataset, sorts them in ascending order, and selects the first K examples [21]. In classification tasks, it assigns the most common label among the K examples to the query example. In classification tasks, it assigns the most common label among the K examples to the query example. In regression tasks, it assigns the mean value of the labels of the K examples to the query example. The choice of K, the number of neighbors to consider, is a critical factor in the performance of the algorithm. In this work, the K parameter was selected after multiple iterations, and we selected the K which gave the best metric results.

2.4. Ridge regressor

Ridge regression is a remedial measure taken to alleviate multicollinearity among regression predictor variables in a model. Often used in machine learning, it is a technique for analyzing multiple regression data that suffer from multicollinearity. By adding a degree of bias to the regression estimates, Ridge regression reduces the standard errors [22].

3. RESULTS AND DISCUSSION

As mentioned before, this paper aims to set a performance comparison between the algorithms and then reveal their importance and powerful characteristics. The added value of this work lies in the machine learning algorithms; in this work, we tried to shed light on future algorithms to add them to the list of those used for EV charging behavior predictions and provide our contribution to the existing literature. Table 1 reveals the results obtained for the four algorithms used in this work.

Table 1. Metrics comparative results of AI algorithms

	MAE (kWh)	MSE (kWh)	MAPE (%)	Execution time (min)
KNN	4.85	38.29	0.23	0.14
XG-Boost	4.20	33.66	0.23	5.85
Random-Forest	4.33	35.85	0.24	20.82
Ridge-Regressor	5.04	41.22	0.26	0.14

In this analysis, we examined the performance of different models based on various metrics. The table provided includes the MAE, MSE, MAPE, and execution time for each model. Among the models, XGBoost demonstrated the best accuracy, as it achieved the lowest MAE and MSE values of 4.20 kWh and 33.66 kWh, respectively. This indicates that XGBoost is more effective in predicting energy consumption compared to the other models. In terms of execution time, random forest had the longest duration, taking 20.82 minutes to complete. In contrast, KNN and ridge regressor had relatively shorter execution times of 0.14 and 0.88 minutes, respectively. It is important to note that the choice of the best model depends on the specific requirements and priorities of the task at hand. If accuracy is the primary concern, XGBoost would be the preferred choice. However, if execution time is a critical factor, KNN or ridge regressor might be more suitable options. This analysis provides valuable insights into the performance of different models and can guide decision-making in selecting the most appropriate model for energy consumption prediction.

3.1. KNNeighbors

Figure 4 illustrates clearly the comparison between the real energy consumption of the EV charger and the predicted load curve, and as the figure shows, the two load curves have high similarity, which confirms the obtained results in terms of metrics. The forecast for the upcoming year, 2024, is visually represented in Figure 5. This graphical illustration provides a projection of anticipated trends and values for the period in question.

3.3. XGBOOST

Figure 6 represents the actual and forecasted energy consumption by the same EV charger in 2023. Visually, we can notice that the similarity is medium and doesn't illustrate the real consumption pattern, especially for the low consumption values. Figure 7 represents the predicted energy consumption for 2024, and as shown in the figure, there are too many fluctuations, which is a little bit far from reality.

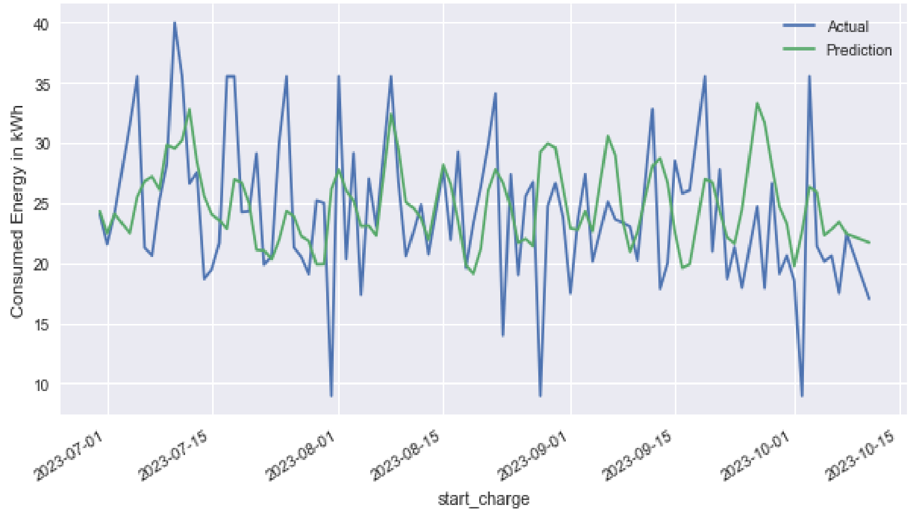

Figure 4. Actual and prediction of energy consumption using KNN

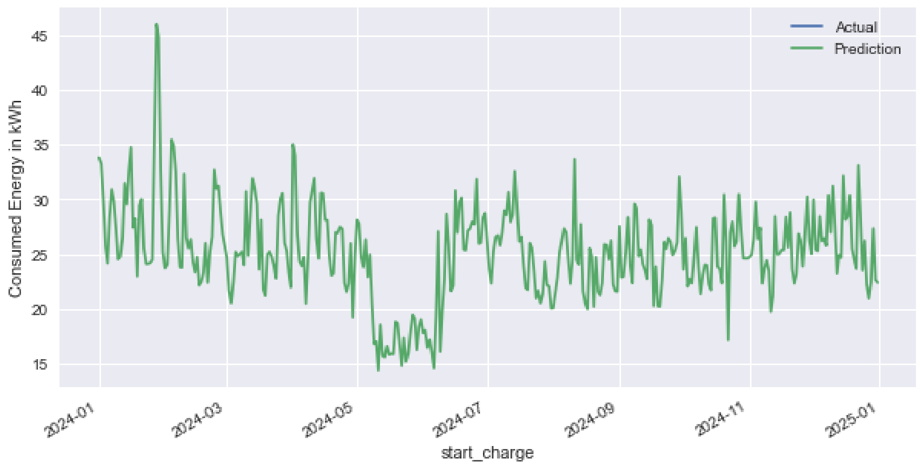

Figure 5. Prediction of energy consumption for 2024 using KNN

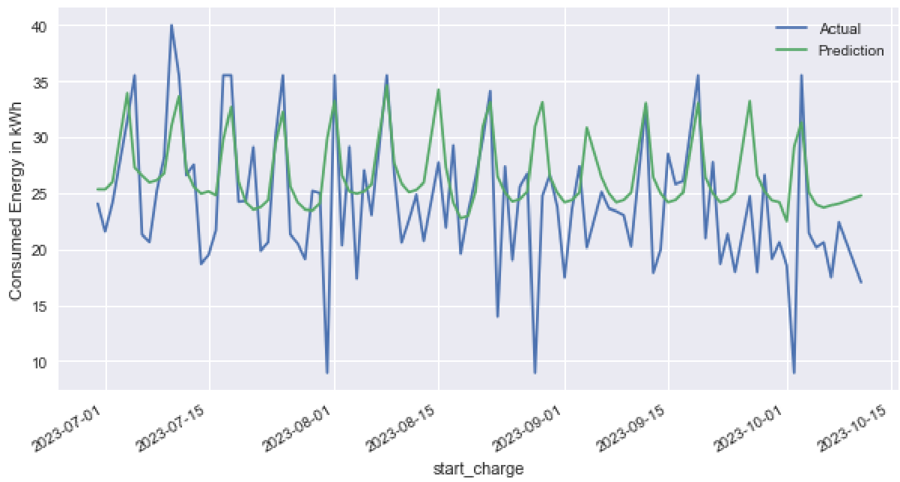

Figure 6. Actual and prediction of energy consumption using XGBOOST

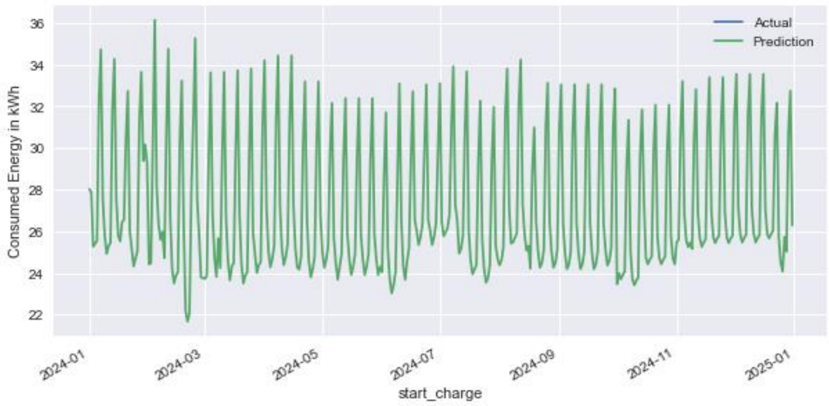

Figure 7. Prediction of energy consumption for 2024 using XGBOOST

3.4. Random forest regressor

For the RF algorithm, the results obtained are illustrated in Figure 8, which is very similar to the results obtained by XGBoost, and this is coherent with the results in Table 1, which are very close to each other in terms of MAE, MSE, and MAPE. Figure 9 reveals the prediction for 2024 energy consumption, and in turn, it is very similar to the RF 2024 energy consumption prediction as illustrated in Figure 7.

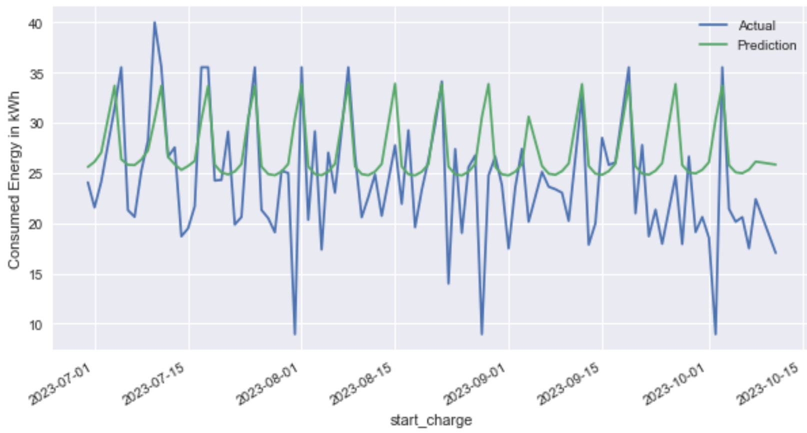

Figure 8. Actual and prediction of energy consumption using random forest regressor

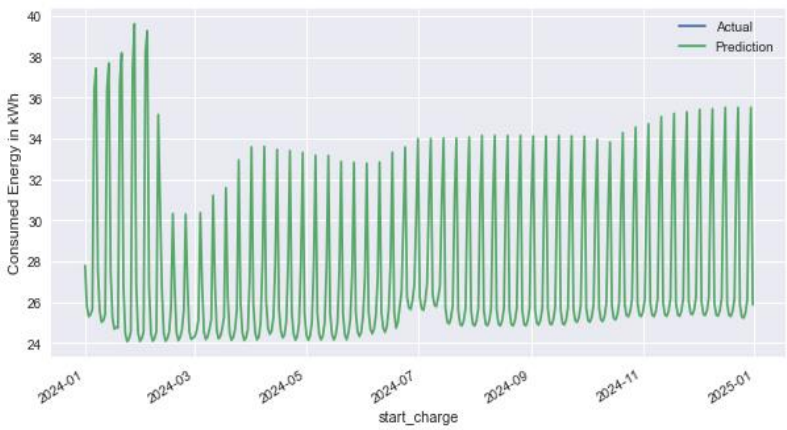

Figure 9. Prediction of energy consumption for 2024 using random forest regressor

3.5. Ridge regressor

Figure 10 displays the outcomes of the ridge regressor algorithm. The figure reveals a significant discrepancy between the actual energy consumption curve of the EV charger and the predicted load curve. This lack of alignment corroborates the poor performance metrics obtained for this model. Figure 11 illustrates the projected energy consumption for 2024. The graph exhibits considerable volatility and an increasing amplitude in the predictions. These characteristics suggest that the forecast may be unrealistic, as such extreme fluctuations and escalating patterns are unlikely to represent real-world energy consumption trends for EV chargers accurately.

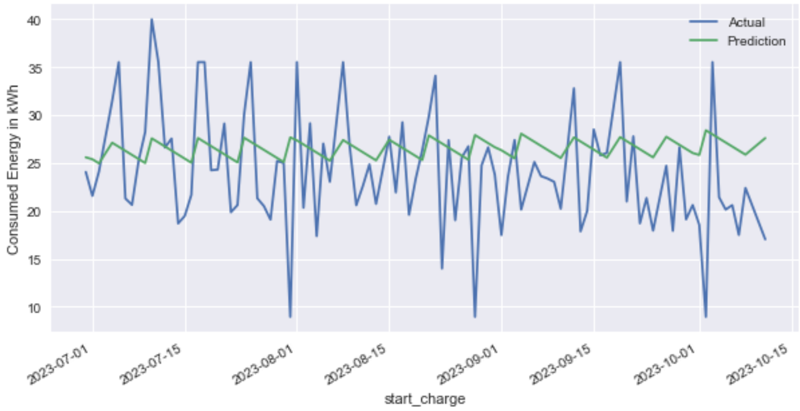

Figure 10. Actual and prediction of energy consumption using ridge regressor

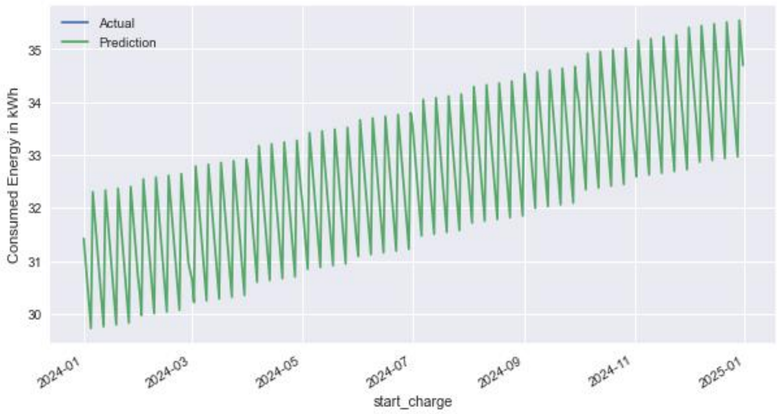

Figure 11. Prediction of energy consumption for 2024 using ridge regressor

In Figure 10, we have provided a comparison between the actual and predicted data for each algorithm used. Additionally, we have included the energy consumption prediction for the year 2024 for the electric vehicle charger under study. These figures allow for a comprehensive analysis of the performance of the algorithms and provide insights into the accuracy of the energy consumption predictions. Figures 4, 6, 8, and 10 illustrate the actual energy consumption and its predictions for an electric vehicle charger in 2023 using various AI algorithms. Visually, the KNN algorithm appears to be the most accurate, showing only minor differences, as it closely aligns with the actual consumption curve. This high similarity indicates its superior performance compared to the other algorithms. Figures 5, 7, 9, and 11 showcase the forecasted energy consumption for 2024. These predictions were generated by supplying a daily list of dates for 2024 to a specially developed Python program. This program utilizes algorithms that have been trained to predict future energy usage effectively.

In comparison with other research, the results in [23] reveal that RF outperforms CatBoost and XGBoost by giving the lowest R^2 and MAPE and then comes ExtraTree and light gradient boosting machine

(LGBM), and in [24], authors found that the suggested long short-term memory (LSTM) model demonstrated superior performance compared to other deep learning architectures, including bidirectional long short-term memory (Bi-LSTM), gated recurrent unit (GRU), and recurrent neural network (RNN). The LSTM model exhibited impressive accuracy metrics. These results underscore the LSTM model's effectiveness in forecasting tasks within this particular context. Additionally in [25] when authors analyzed macro-data with simple patterns, the autoregressive integrated moving average (ARIMA) model with regressors outperformed other methods, followed by trigonometric, box-cox transform, ARMA errors, trend and seasonal components (TBATS), artificial neural network (ANN). This suggests that for straightforward macro-level data, traditional statistical approaches and simpler machine learning models may be more effective than complex deep learning techniques.

This study compared machine learning models for predicting energy consumption in EV chargers, evaluating their performance using various metrics. Its significance lies in providing practical insights for energy management, supporting grid resource planning, and advancing predictive modeling in the sustainable transportation sector. By offering model comparisons, 2024 forecasts, and benchmarking against other research, the study aids decision-makers in selecting appropriate models for energy consumption forecasting, contributing to more efficient and sustainable practices in the expanding electric vehicle industry.

For power distributors, it's imperative to have an in-depth understanding of the load profile of each electric vehicle (EV) charger to optimize energy management during high-demand periods [26]. This necessitates the formulation of a characteristic consumption curve for each EV charger in residential and non-residential sectors [27], or a cluster of analogous chargers, predicated on congruent consumer load profiles [28], [29].

4. CONCLUSION

In summary, this research focuses on demand-side management by predicting future energy consumption for EV chargers, addressing a gap in the literature. By employing machine learning algorithms and statistical modeling, the study forecasts EV charging demand for 2024, providing insights that can be generalized to other types of chargers. The comparison of algorithms, including KNN, XGBoost, ridge regressor, and random forest, reveals that KNN offers superior accuracy in predicting EV charging behavior. These findings are significant for distribution operators, as they help manage the balance between energy generation and consumption, preventing grid issues like overloads. The research contributes to the field by offering a reliable method for predicting EV charging demand, aiding in efficient energy management.

As a progression and extension of this research, we envisage working on load profiling. This paper will leverage the same dataset and will integrate clustering algorithms to further refine our understanding of EV charger load profiles. Clustering algorithms will allow us to identify and group similar load profiles, enhancing the granularity of our insights and allowing for more tailored energy management strategies. This extends our contribution to the field by providing a more nuanced understanding of consumption behaviors and offering robust tools for energy management in the context of EV charging.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [Ayoub Abida]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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BIOGRAPHIES OF AUTHORS

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