Optimized Real-Time Energy Prediction for EV Power Stations Using Hybrid Algorithms- A Review

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ABSTRACT: The rapid increase of electric vehicles (EVs) has significantly impacted global energy consumption, which presents unique and new challenges for predicting energy demand for charging of these vehicles. Models that predict accurately are essential for optimizing utilization of charging stations and that also ensures grid stability. This review paper critically examines a wide variety of techniques that are used for prediction, including statistical approaches such as autoregressive integrated moving average (ARIMA) and Kalman filters, and also machine learning methods like support vector machines (SVM), Bayesian extreme Machine learning machines (BEML), and it also analyses advanced deep learning models such as long short-term memory (LSTM) networks and hybrid frameworks. Key factors that influence EV charging demand are vehicle conditions, state-of-charge (SOC), driving patterns, distance-to-destination and geographical characteristics—are studied. After all these advancements, there are still challenges that need to be focused, like data heterogeneity, computational complexity, and scalability. This study summarizes existing works and highlights the effectiveness of novel integrated models, including empirical mode decomposition (EMD), optimization algorithms, and neural networks. These kinds of studies aim to guide the development of robust, scalable, and prediction systems that are real-time and support energy distributors to manage EV charging infrastructures effectively.

Keywords: ARIMA; Kalman filter; LSTM; Machine Learning; Electric Vehicle; Charging Stations

1. INTRODUCTION

Electric Vehicle adoption is gradually becoming one of the stronger disruptors on the global energy map. These have been an outcome of improvement in Electric Vehicle technology, steps toward regulatory action to safeguard the environment, and growing demand for eco-friendly alternatives in the transportation sector. To overcome these issues, the demand for charging electric vehicles (EVs) needs to be predicted with high accuracy, and thus, several methodologies have been proposed. Simple statistical models like ARIMA and Kalman filters are often used because they are easy to understand and interpret [1]. However, these models usually neglect the fact that real EV behavior is often nonlinear and dynamic in nature. On the contrary, machine learning methodologies like SVM, ANN, and LSTM are said to offer higher precision and robustness due to the capacity to detect complex relationships between the data[2-3]. Despite their promise, these approaches face several challenges. The statistical models often suffer from scalability problems and are not easily accommodative of heterogeneous data whereas machine learning methods require intensive computational power along with enormous datasets. Furthermore, the non-availability of real-life data, as driver behavior, vehicle state, and charging patterns can be very private, hampers model development further [4]. Hybrid and optimization-driven techniques, deep reinforcement learning and empirical mode decomposition (EMD) along with sophisticated neural network architectures, have recently been advanced to overcome these challenges. These methodologies have shown the potential to enhance predictive accuracy and manage nonlinear dynamics; however, they are computationally demanding and dependent on historical data [5].

This paper summarizes existing research into the demand forecasts for EV charging, in relation to the classical and modern developed techniques. Organized the paper are Section 2, describes the literature review and previous works and motivation for research, Section 3 briefly describes the construction of this newly proposed predictive model and specifies data used in this study; Section 4 discusses challenges faced during research; and proposed solution is in Section 5 while conclusions drawn from this paper summarize final insights at the last Section 6.

2. LITERATURE REVIEW

Charge management as an electric vehicle represents, perhaps, one of the newest challenges to come out due to worldwide adoption of electric vehicles. Great approaches would better predict charging station infrastructure through provision towards grid reliability and efficient access points for energy usage. Hence, a variety of different methodologies has been designed around statistical models, machine-learning approaches, and hybrid approaches toward this end. Despite considerable progress, several inconsistencies and gaps persist in existing research, necessitating a comprehensive review.

It's actually primarily due to the simplistic model presentation and ease of use when making interpretations. Historical evidence shows that short term forecast predictions have used several varieties of autoregressive integrated moving average, or ARIMA. Indeed, Amini et al. (2016), utilizing time-series data, were in particular efficient for projecting charging demand for isolating seasonal and time variation content factors. However, the reliance of ARIMA on stationarity assumptions limits its ability to effectively handle nonlinear and time-varying datasets, such as those involved with meteorological factors or individual driving habits [6]. Kalman filters have been implemented in various forecasting cases of the electric vehicle charging demand. Researchers applied the combination of Kalman filters with autoregressive models in the forecast of EV charging loads, and hence were able to detect short-term fluctuations and temporal trends. This integration of approaches thereby ensured some accuracy in the forecasting since the Kalman filter does allow for the state's prediction within dynamic systems thereby resolving noisy data and uncertainties in a single instance. The method holds mainly to the applications having charge sessions pretty frequently or have variable demands as the case may be with the provided system. However, despite these strengths, the Kalman filters have very considerable limitations that prevent them from becoming more widely applicable [7]. Some of these limitations are overcome by advanced statistical models like the Trigonometric, Box-Cox, Auto-Regressive-Moving-Average, Trend, and Seasonality (TBATS) model. TBATS is particularly effective at handling complex seasonal patterns as reported. Its strengths notwithstanding, TBATS is unable to account for the nonlinear interactions present in heterogeneous datasets typical of EV charging demand [1,8].

Many used SVM for the prediction of energy consumption. The presented evidence showing that SVM can be utilized in catching the model of EV energy demand moderately well. However, SVM tends to be unfriendly for scaling and usually experiences vast parameter tuning-that's an advantage, especially while holding big and diversified data-sets [9]. ANNs have been extensively utilized to predict electric vehicle charging demand. The applied supervised learning towards the prediction of energy consumption by EVs by extracting statistical features from the pattern of charging. ANNs, although more accurate compared to their traditional counterparts are often targeted for their "black box" nature which doesn't provide much interpretation and is also prone to overfitting when employed in domains with very meager data [10-11]. The weakness of this approach is that it relies on historical data, meaning the LSTM model only learns from the lessons of the past trends but, in reality degrades the precision of predictions of situations characterized by sparse or unpredictable variability-like when an unaccounted for event occurs or abrupt policy changes alter the demand to charge. Another challenge is large and high-quality labeled data that is needed in places where the EV charging infrastructure is nascent or underdeveloped. [12].

3. ANALYSES OF PROPOSED APPROACHES

Propose a comparative study of time-series-based models that include Trigonometric, Box-Cox, ARMA, Trend, and Seasonality, Auto-Regressive Integrated Moving Average, Artificial Neural Networks, and

LSTM for the prediction of EV charging demand. The performance metrics like Mean Squared Error are used for evaluating the models, providing critical insights toward improving electric vehicle charging infrastructure and energy management [13]. The research employed a dataset from Georgia Tech, Atlanta, achieving a prediction accuracy of 97.14%, a Mean Absolute Error of 0.1083, and a Root Mean Square Error of 2.0628×10^{-5}. The study emphasized the effectiveness of the EMD–AOA–LSTM approach in addressing challenges such as vanishing gradients and optimizing prediction metrics, demonstrating its superiority over traditional prediction techniques for EV charging demand forecasting [14]. Hybrid approaches consisting of a mix of technique(s) with SARIMA + LSTM were also presented in the study. These models' data come from both simulated and real-world datasets. It uses historical EV charging demand data from regions like the USA, China, and Finland. Key variables include the time taken to charge the session, rates of energy consumption, and traffic patterns. To test the effectiveness of the models, metrics like MAE, RMSE, and R-squared are used. In comparison, hybrid methods would be more accurate and able to understand both linear as well as nonlinear relationships underlying electric vehicle energy demand [15]

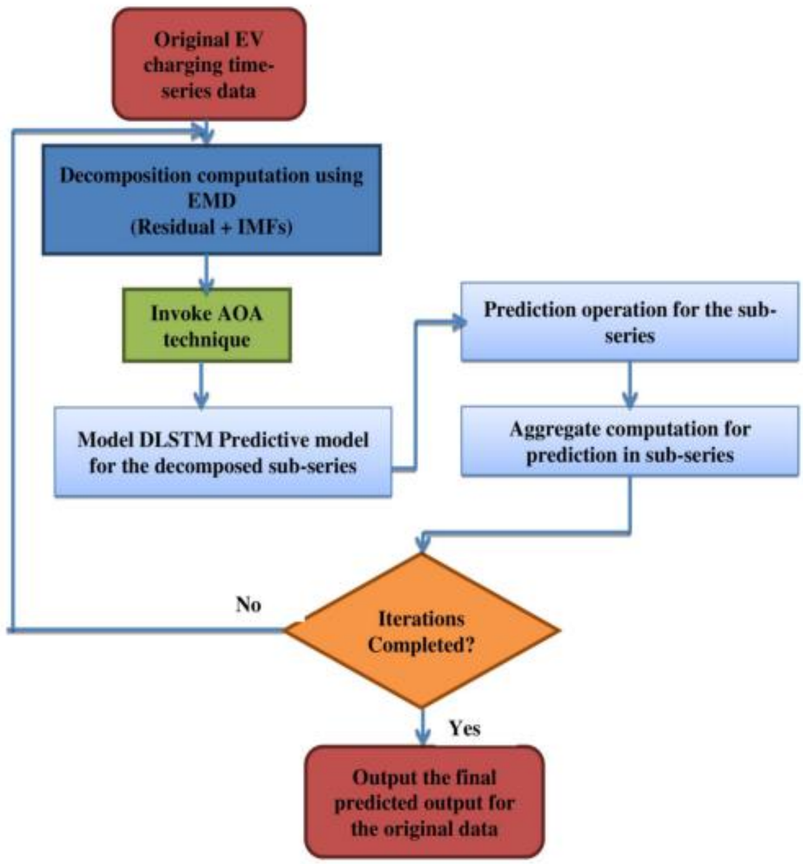

Figure 1. Flow diagram of the combined EMD–AOA–DLSTM predictor model

The hybrid model that is illustrated in the flowchart combines the EMD, AOA, and DLSTM together towards the forecasting of EV charging demand. The raw EV charging time-series data decomposed into its intrinsic mode functions and the residual components using the EMD, which are said to enhance feature extraction capabilities for the data. The AOA is then used to tune the parameters of the forecasting model so that the precision of the forecast improves. Then, the decomposed sub-series are fed to the DLSTM model to perform predictive analysis on every sub-series. All of the predictions from the sub-series are aggregated to make a complete forecast. An iterative process refines the predictions until the desired precision is achieved, and an outputted final aggregated forecast is obtained. This methodology aptly employs decomposition, optimization, and deep learning techniques for accurate electric vehicle charging demand prediction. [16]

4. CHALLENGES

Even with remarkable advancement of techniques of the past several decades, recurrent issues in these approaches include the following:

- Most of the models such as ARIMA and Kalman filter failed to capture the non-linearity and heterogeneity of data EV charging patterns.
- The advanced techniques such as LSTMs and hybrid models involve high computational powers hence inappropriate uses in real-time applications
- Most models have been tested on rather small datasets, which has become their performance in varied geographical as well as operational contexts.
- Deep learning models, such as ANNs and LSTMs, usually look opaque, thereby making them so challenging to derive actionable insights for policy and infrastructure planning.

5. SOLUTION

Modeling EV charging patterns remains problematic despite decades of tremendous technology innovations. The incapacity of models such as Kalman filters and ARIMA to imprisonment heterogeneity and non-linearity can be addressed by hybrid methods that combine deep learning models, like LSTMs, with conventional techniques. The understanding of various charging performances can be further improved by ensemble learning and domain-specific feature engineering. Optimization strategies like model pruning, lightweight frameworks, and edge computing can be used to get about the high computational demands of sophisticated methods like LSTMs and hybrid models, making them suitable for real-time applications. Model quantization and refinement are two methods that can be used to produce effective varieties of these models. Creating and distributing big, diverse datasets that reflect a range of operative and geographic contexts might help solve the restricted applicability of many models caused by small dataset testing. Procedures for data augmentation can help datasets produce even more, and industry-wide collaboration can help standardize data for enhanced generalization. Improving the interpretability of deep learning models like ANNs and LSTMs is vital for providing useful information for infrastructure and plan development. Interpretable surrogate models mutual with explainable AI systems like SHAP and LIME can make model predictions more comprehensible. Decision-makers might also benefit from intuitive control panel that incorporate visual descriptions. With the help of these fixes, EV charging configuration models may become more reliable, scalable, and valuable in practical states.

6. CONCLUSION

A number of methodologies that have been applied are critically reviewed to predict demand for charging electric vehicles, strengths and weaknesses, and avenues for future development. The traditional statistical models ARIMA and Kalman filters prove very useful for short-term predictions but are not that good in capturing nonlinear dependencies or long-term forecasting. Machine learning techniques, particularly SVM, ANN, and LSTM, have been more precise in capturing complex patterns and time dependencies in the demand of EV charging. These methods, however, are computationally intensive and require large datasets for training purposes, thereby limiting their applications in practical real-time systems. Ultimately, it will be very important for the integration of electric vehicles into smart grids and the optimization of charging infrastructure to have an accurate and efficient EV charging demand forecasting model. By addressing the gaps and limitations as identified here, a pathway toward more reliable, scalable, and practical forecasting models will be opened that can catalyze the management of EV energy consumption toward a more efficient outcome.

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