AIP Conference Proceedings

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Cite as: AIP Conference Proceedings **2527**, 040001 (2022); https://doi.org/10.1063/5.0109161
Published Online: 14 October 2022

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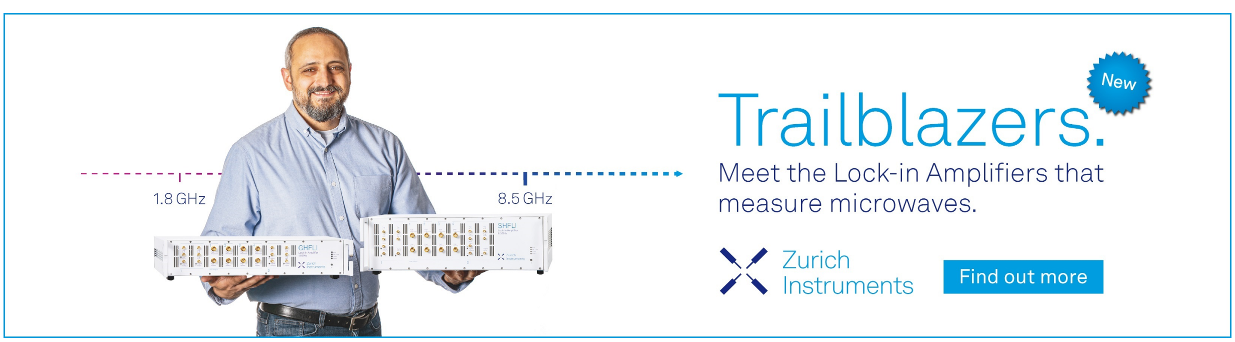

AIP Publishing

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Deep Learning Enabled Smart Charging Technology for Electric Vehicles

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Abstract. Reliability, efficiency, and cost-effectiveness of smart grids are enhanced with power demand softening by means of efficient load management in electric vehicles. In such initiatives, the involvement of EV users may reduce due to the lack of adaptable user-centric approaches. During the connection sessions, the EV charging time is determined using a deep learning algorithm-based smart charging strategy proposed in this paper. Here, the total energy cost of the vehicle is minimized by making charging decisions considering demand time series, pricing, environment, driving, and other auxiliary data. The memorization technique is used for the estimation of the optimal solution of the existing connection sessions in the initial stage. The deep learning models are trained with this existing data and optimal decisions to make suitable decisions in real-time scenarios where car usage or future energy price values are undetermined. A significant reduction in the charging cost is observed by training the neural network with the proposed model. The results obtained are compared to the optimal charging costs computed and are found to be closely similar.

Keywords: Deep learning, Convolution neural network, smart charging, Electric Vehicle, Minimization

INTRODUCTION

Energy efficiency is attained by influencing the energy consumption pattern using incentive-based techniques on the smart grid [1] through demand-side management (DSM) [2]. Additional energy generation capacity is achieved with minimal investments while meeting the energy demands by efficient utilization of the existing infrastructure [3]. Dynamic prices and other economic incentives are achieved by integrating electric vehicle (EV) charging with DSM as the normal charging schemes may inflate the demand peaks and overload the power grid with an increase in EV adoption [4]. The participation of EV users in DSM programs is reduced considerably as they lack knowledge regarding responding to time-varying prices as observed in recent studies. Centralized and decentralized stanMToints [5] are considered while studying the EV smart charging schemes.

International Conference on Advancements in Materials and Manufacturing Engineering – ICAMME 2021
AIP Conf. Proc. 2527, 040001-1–040001-7; https://doi.org/10.1063/5.0109161
Published by AIP Publishing. 978-0-7354-4202-3/$30.00

Driving habits, electricity cost, and other behavioral, as well as environmental variables, help in the prediction of future states for solving the issue of smart charging in conventional decision-making schemes. Further, these predictions are used for making optimal decisions [6]. Perfect comprehension of the future is essential to ensure the optimality of these decisions. When the predicted values vary in a significant manner, difficulty is encountered in the decision-making aspect. When it is likely to incur different outcomes, prediction uncertainty [7] cannot be taken into account. This paper proposes a complete learning technique that optimizes actions and predictions simultaneously rather than enhancing the prediction model. Real-time decisions are allowed in any context in the deep learning approaches that enable meeting the goals and requirements of EV users by providing them the required flexibility [8]. The need for analytic and hand-crafted decision functions found in conventional systems is removed making the model less time-consuming. The prediction function is analyzed based on its strengths and weaknesses automatically in the proposed decision function. User-specific data [9] is used for training the model where the system learns the personalized decision functions.

A complete demand response strategy is proposed in this paper for minimizing the EV's overall energy cost based on the real-time pricing by controlling the EV charging using a deep learning algorithm. A discrete-time interval charging control method is modeled using the Markov Decision Process (MMT) [10] framework initially. The set goal is attained by the decisions that are made based on the actions. The memorization technique is also used to overcome certain challenges [11] assuming complete information is available regarding the time and distance of the trips, fuel and electricity prices, current and future states, and so on. Complex inputs can be mapped properly using the data history function into the current state for efficient charging decisions. Learning is desired from the memorization function and its corresponding optimal actions. Cost comparison of various other deep and machine learning algorithms such as k-Nearest Neighbors (KNN) [12] and Shallow Neural Network (SNN) [13] is performed along with the proposed deep learning model. Threshold-Based Rule (TBR) [14] and Always Charge (AC) [15] baseline models are provided additionally. Here, electricity price is set as a threshold for decision-making. The memorization-based optimal offline solution is compared with these models. From the results of the comparison, it is evident that without the need for future knowledge, the memorization technique is able to provide more optimal decisions. Hence in real-time decision making, the deep learning model outperforms the other conventional techniques.

RELATED WORKS

Coordination perspectives in a centralized and decentralized manner may be implemented for organizing the DSM and EV integration framework. Electric load profile valley-filling, load variation minimization, load factor maximization, power loss reduction, charging cost reduction, generation cost maximization, and voltage or frequency regulation are some of the varied objectives observed in the existing literature. An optimal solution is attained with a large amount of data corresponding to prior knowledge that helps in managing the EV charging via aggregator, smart grid, or other single agents in a centralized perspective [16]. The EV owners are assumed to have total control over the choice of charging in a decentralized perspective. They can respond effectively when there is a variation in price signals and participate in DSM programs making use of the available flexibility. Time-of-Use (ToU) pricing and other flat rates adopted in DSM programs for EV users are overcome with dynamic prices where the volunteer participation is provided with incentives. During off-time periods, the EV charging peak is prevented by EV users and utilities using cost-effective solutions like real time pricing. This scheme is more efficient than the conventional flat rates. The EV usage cost is reduced considerably by optimization of the EV charging schedule. Precise future data is the only means to achieve an optimized schedule. However, such speculation is risky, unscalable, impractical and cannot be based on the actual requirements of the EV users. This leads to inefficient schedules [17].

In several fields with complex problems, astonishing results are observed due to the prominent algorithmic and hardware advancements involving deep learning. In diverse areas involving natural language processing, computer vision, and so on, deep learning is a disruptive approach. Deep learning technologies are obtaining attention with recent efforts and time-series analysis. Several researchers have used deep learning algorithms for prediction and forecast of energy consumption [18] as well as short term load [19]. Time-series classification issues are also addressed with deep learning techniques. In this paper, the conventional strategies are compared with the recent deep learning algorithms and their convergence is used for addressing decision making problems in EVs for smart charging and smart appliance DSM [20].

PROPOSED METHODOLOGY

A novel methodology is presented in Figure 1 which is used to build a decision making model that can be used to estimate the pricing of electricity for charging the electric vehicle. A number of experiments are conducted indicating the various sources used along with other information. Here MMT and MT modelling [21]are used in the optimization stage to determine the best solution. Optimal solutions and their historical datasets are used to determine testing and training sets using the information system. The datasets are used to train the learning models with the help of DL algorithms.

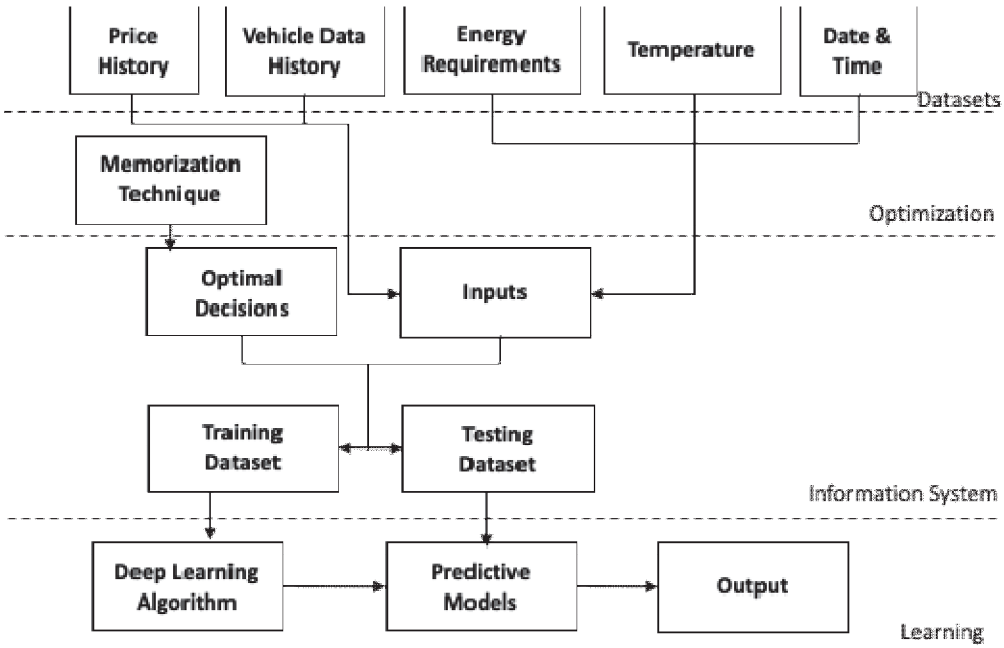

FIGURE 1. Architecture of Proposed Framework

A. Datasets

Data from 20 conventional cars are collected and GPS-based usage data are observed. The database includes maximum allowable speed, actual speed, position, time, date and number of the vehicle's location measured at a time granularity of a second. The maximum distance travelled in winter and summer are observed, based on which the charging sessions and trips are simulated for the electric vehicles. A comparison between the different specifications of the PHEV vehicles is determined.

B. Optimization

The aim of the smart charging vehicle is to determine the best EV charging schedule that can be followed at every interval of time within a specific duration when the electric vehicle is plugged in. This will decrease the overall energy cost of the system, based on the requirements of the EV owner.

C. Information System

Probabilistic methods are used to model the information that is used in optimization methods. Forecasted and random variables are incorporated in this methodology which leads to space for uncertainty. In order to tackle this problem, an information system is built which leads to diverse and real data for deriving patterns with the DL algorithm.

D. Learning

Based on historical databases, Memorization Technique will pave the way to optimal decision making based on variable discretizations. However, this is based on the consideration that future values as well as present values of environmental and car data is known in advance. Here label historical databases are used instead of MT along with state space representation. Standard supervised learning algorithms are used along with labelled data to identify models which can be used to make real-time decisions based on the requirement of determining when to charge the vehicle. This methodology paves way to primary recasting of the decision making issue wherein the optimal action is identified based on the novel observation. Deep Neural Networks, Shallow Neural Network, k-nearest neighbours and Threshold-Based Rule are the principal learning methods used.

EXPERIMENTAL RESULTS

Fig.2, Fig.3 and Fig.4 represent the operational cost of charging during three seasons namely summer, winter and spring respectively. They also represent the time interval length observed for 15 bins. It is found that in all three scenarios, efficiency of the system increases when the interval of 15 minutes is used instead of an interval of 60 minutes. This is primarily because the decision-making process is made easier with small time frames. Moreover, there is also a significant increase in the complexity of the model. The size of the datasets as well as the computation time required increases in a linear fashion with respect to the bins that are involved. One of the frequently used strategies is that of the AC model which charges the vehicle immediately when it is parked, given that the battery requires charging. It has been observed that there is significant saving in energy cost during the summer when using the AC model. Moreover, the peak energy prices and the charge periods are dependent on each other. Hence, it is observed that when using MT and AC model, the outputs are inversely proportional to that of the total distance that the vehicle has travelled.

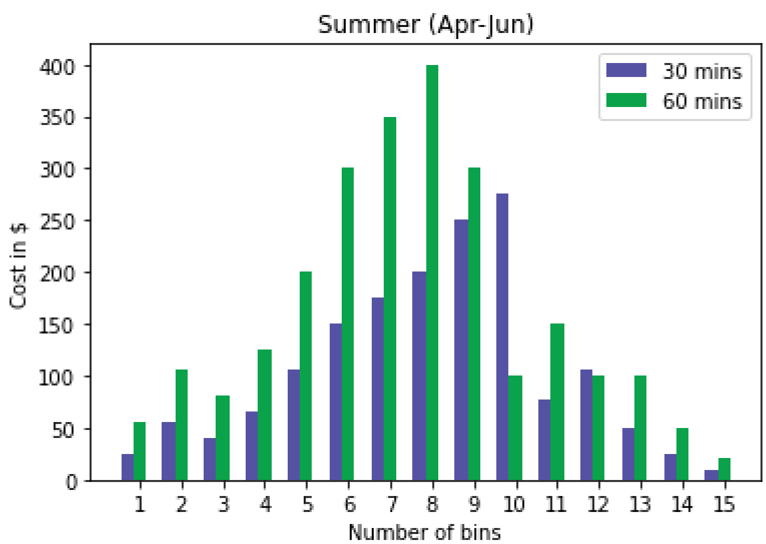

Figure 2. Average cost during summer training periods for the different number of bins by t

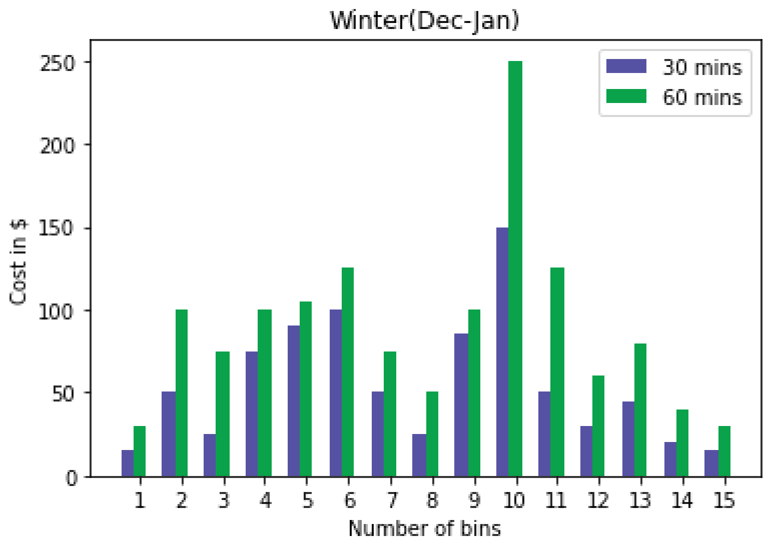

Figure 3. Average cost during winter training periods for the different number of bins by t

A ratio between the MT saving and ML model is also observed, based on the amount of gasoline used. For optimal efficiency, a value of 1 is indicated which is not possible to be attained in real-life scenarios. Hence a value that is close to 1 will be used as an equivalently efficient methodology that is able to meet the demands of electric vehicles.

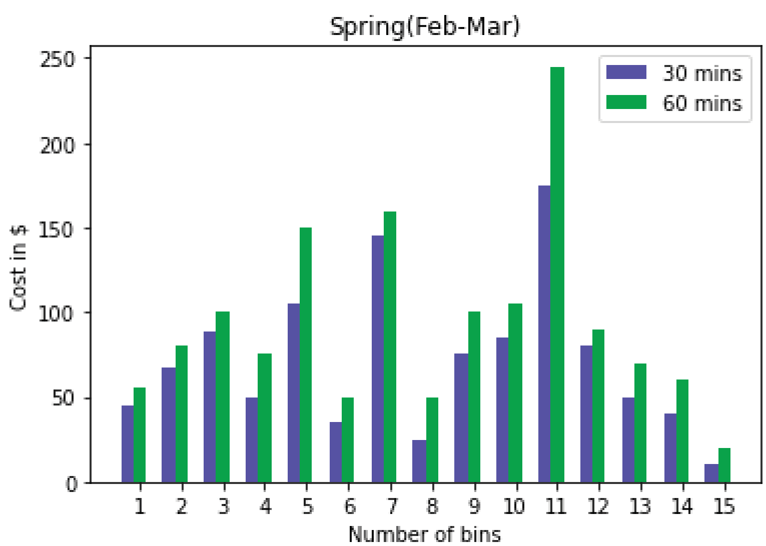

Figure 4. Average cost during summer training periods for the different number of bins by t

CONCLUSION

In this work, a novel methodology is used to determine charging of an Electric vehicle based on the vehicle's current state, without taking into consideration variables like amount of energy required, time of connection, demand and electricity price. The two major principles behind this model are: optimal actions that are used in collision with the information system and optimal actions that are removed based on information about the future analysis. Based on these conditions, the battery model will coincide with the one used in the EV. Along with Deep Neural Network (DNN), Shallow Neural Network (SNN) and k-Nearest Neighbours are also used to evaluate the performance of the DL model. As future work, this methodology can be used to analyze the impact of vehicles on load curve and also decide charging factors with the help of game theory.

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