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Real-time Electric Vehicle Load Forecast to Meet Timely Energy Dispatch

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***Abstract*—Electric vehicles are more eco-friendly and energy efficient than the conventional internal combustion engine vehicles. This technology adds new challenge to the existing energy distribution network. Specifically, electric vehicles are allowed to start charging their batteries the moment they are parked into a charging lot which creates a unpredictable load on the energy distribution network. Ideally, the energy supply system must always be in a state where the amount of energy consumed is equal to the amount of energy produced. This priori is also for the reduction of energy wastage. Hence, load forecasting serves as an estimated preemption for the supply system. In this paper, time series techniques for electric vehicles' load forecasting are proposed. Experiments are given using Singapore's energy dispatch system. A framework to provide the relevant electric vehicles' load forecast to fulfill the timing criteria is also proposed.**

I. Introduction

In this new millennium, global warming and conservation has been foremost issue of many governments [1]. Excessive release of greenhouse gases from various human activities was deemed the main cause of global warming by the intergovernmental panel on climate change (IPCC) [2]. As shown in Fig. 1, from 1880 to 2012, the global average temperature, inclusive of continental and oceanic, has risen by 0.85 °C and it is expected to further increase by 2.4 °C by 2020. Global warming causes are linked to natural disasters and many countries have agreed to reduce their greenhouse gases emissions [1].

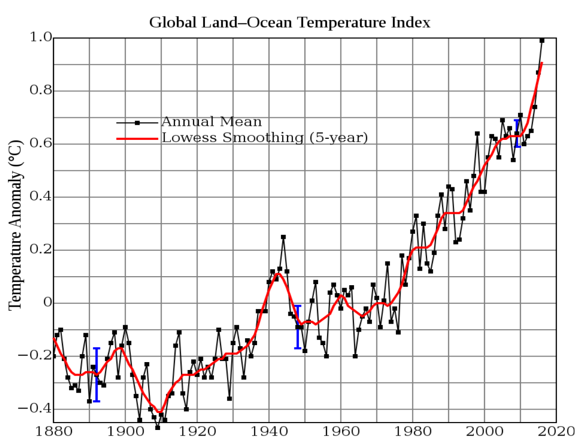

Fig. 1. Rising global temperatures from 1880 to 2012 with NASA projection from 2012 to 2020. Image source: NASA [3].

Greenhouse gases are made up of carbon dioxide, methane and nitrous oxide; carbon dioxide (CO_2) being the largest in production [4]. One of the main contributor of CO_2 has been the burning of fossil fuels [5]. Technology has vastly reduced its emission since its beginning in the industrial revolution [6]. However, there still exist a sizable CO_2 production in the world; internal combustion engine vehicles (ICEV) or motorcars [7]. ICEV has a energy conversion efficiency at 10-50% [8] whereas the electric vehicles (EV) has it at 30-99.9% [9]. It is estimated that CO_2 emission of an ICEV is 411g emission per mile or 257g emission per kilometer [10] and the estimated CO_2 emission is 70g emission per kilometer for electric vehicles [11].

Given the current emission situation, it is no surprise that curbing climate change emission gases has become one of the primary motivation auto-manufacturers to build EV [12]. They get energy from the energy distribution system, better known as the *power grid* (PG). The EV is able to recharge at any point of the grid. However, its expected load is not known until the point of charging. This unexpected temporal and spacial energy load poses a challenge for the PG. This is because the amount of energy input into the PG must always be equal to the amount of load.

Likewise, this is also a problem for retailers that requires forecast information to meet energy trade transactions related to the PG. Take for instance the national electricity market of Singapore (NEMS) [13], it can be seen in Fig. 2 that energy is traded half-hourly. In total there are 48 half hourly periods for a day. Each period starts at the zeroth and thirtieth minute of the hour. Demand, uniform Singapore energy price (USEP) and other indices are also updated in the same time interval. 2 provides a graphical view of the relationship between demand and energy prices. Most importantly, it also shows the forecast of all the indices and also finalized values for periods passed. Retailers depends on such information for planning their energy trades. Every retailer has to follow the rules and timing

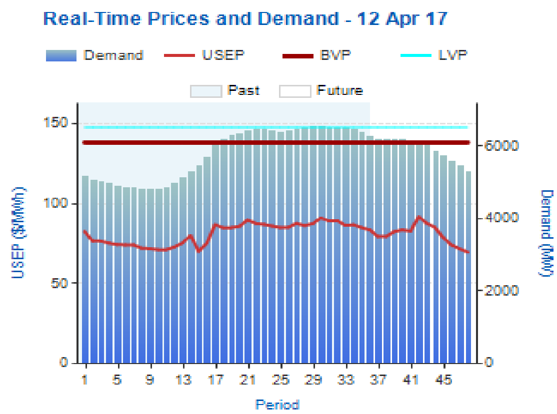

Fig. 2. Daily energy demand versus price. Image source: Energy Market Company, Singapore [13].

cut-offs if they want to participate in the energy market. For example, retailers buying energy has to finalize their bids at $T-4$ minutes where T is the beginning of a energy dispatch period. And the market clearing engine will clear the bids and offers within 4 minutes. Power system operators must dispatch the energy within the 30 minutes time periods. There cannot be energy spill over to the next period for dispatch.

Participants of NEMS will need to work with the latest information to perform energy trades within the same half-hour period. Some participants can simultaneously be the providers and consumers of energy. They are known as *prosumers* [14]. They must optimize both their buying and selling strategy compared to energy generators or consumers. This principle of half-hourly decision and action processes would also apply to all dealings and operations that involves this market; primarily the power systems operators(PSO). The end goal is to provide an approach to choose and approximate the amount of data required to make an accurate forecast within a energy-market dictated time interval.

In recent years there have been much focus using deep learning machines in forecasting. For example, the best results in the European Energy Market 2016 (EEM2016), Price Forecasting competition, were obtained using long-short term memory; a form of recurrent neural networks [15]. Deep learning networks for python have become very user friendly these days. Especially, with tools like Keras [16] and Tensorflow [17], such technologies are becoming more deployable in business; allowing people to improve on their work and not be bogged down by its implementation details.

Since deep learning machines have high computation costs, under given hardware resources it becomes difficult to find the optimal answer within a time limit for real-time world deployment. Moreover, load forecast for electric vehicles is not straightforward as it is affected by traffic conditions, weather and other road-related factors. It also has to fulfill the energy dispatch timing constraint.

In this paper, the approach to use deep learning methods within limited hardware resources and time to forecast EV's load is presented. Past EV's load data is obtained using a multi-agent system simulating EV on a road network. This is then used as inputs to the deep learning methods. We introduce operational time constraints to the approach. We used NEMS as a context for relevancy to the real world. Together with the constraints and input data, we search for the maximal amount of data in terms of data that produces the optimal result as well as satisfy the constraints. Finally, we conclude on the best method for the discussed approach.

II. Existing Solutions

Forecasting has been used for many purposes. Forecasting uses past data to estimate future values or trends. In modern day, forecasting is used in weather, in finance for stock exchanges amongst many others. However, the use of forecasting has been dated back as early as 650 B.C by Babylonians attempting to make short-term weather forecasts [18].

Forecasting has been used in the areas of seismology for earthquake prediction, land re-development for land-use prediction, finance for credit default risks against customers borrowing money and more recently in supply chain management for logistic prediction; forecasting the product to be at the right place and time. Forecasting has become integrated into our daily lives and activities.

Even so, forecasting for EV isn't easy because of two contributing energy loads for the EV; energy consumed for traveling and energy consumed for powering the air-conditioning. The former is determined by driver behavior while the latter by temperature. It is shown in Fig. 3 that weather forecasts are so complex and unpredictable that a 10 days daily temperature forecast has as little accuracy as a similar 5 days forecast. The variance is as much as 10 °F difference on either the 5 or 10 days forecasts, if not more. And even for a day-ahead

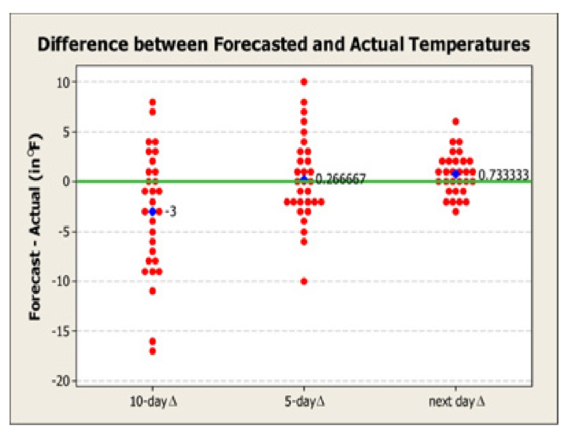

Fig. 3. Variance in daily temperature forecasts as observed in experiments executed by M. Paret and E.Martz [19]. Image source: Minitab [19].

temperature forecast, there is still a difference of at least 6.2 °F [19]. This impacts greatly on the margin of error on EV energy consumption. Forecasting EV load based on estimated information will have even a larger margin of error.

In general, forecasting involves deriving future information from patterns or entropy in historical data. Voyant uses linear regression in solar radiation forecasting to estimate the energy harvest [20]. Auto-regressive integrated moving average with exogenous outputs (ARIMAX) has also been explored in photo-voltaic panels energy output forecasts [21]. Both methods can also be combined with different types of data in Ensemble machine learning to perform the same task [22].

Deep learning has been the main forecasting method used recently; noticeably in the energy price forecast competition 2016" [15]. The winning entry used a deep-learning method called long-short term memory (LSTM). It is a neural network (NN) that is able to adaptively determine if information from an distant or closer past has more effect on the future outcome [23]. This makes it powerful because it can keep track on the information's entropy and determine best when to use it.

Recurrent neural network (RNN) has also gained popularity recently. RNN differs from traditional artificial neural network (ANN) is that its information flow is cyclic and directed; whereas in an ANN it is linear. Its accuracy is determined by a fitness or reward function as opposed to verifying against provided labels that came with the input data [24].

Multilayer perceptron (MLP) utilizes feed-forwarding technique in order to draw relationships between the input data and output results. Commonly, layers are used as intermediaries for information mapping. Learning is supervised through back-propagation [25]. Traditionally, MLP is useful for solving classification problems. However, by labeling time-series data certain outcomes, it can also be used to treat time-series trend analysis as a classification problem and forecast outcomes.

In this paper, an approach to use the various forecasting methods for energy trading will be made. The best method will be selected. It will be based on accuracy of the forecast, time and among of time required for the computation. In order to facilitate its use in timely dispatch of energy from the pool, a time constraint will be placed during the computation.

III. Data

To-date there are no real data detailing change in velocities for the vehicles while traveling on the roads. Therefore, data used for the energy load was obtained from simulations using a traffic multi-agent system called MATSim [26]. For the simulations, we use the road network system of Singapore. The vehicles that use the road network are modeled as agents in here. The number of vehicles and its likely usage are determined according to professional and housing locations in Singapore. This information can be determined from several reports consolidated by Singapore's ministries. The number of cars traveling on the roads is found in vehicular figures documented in annuals from the ministry of transport. The homestead locations of the agents are divided accordingly to population census from Singapore's department of statistics. The workforce distribution of people residing in Singapore can be found in reports from the ministry of manpower.

Agents are intelligent entities that are capable of interacting with their surrounding environment. They interact after self-deciding the next action after sensory observations of their environment. In this research, the agents are car-owners of a city or country. The different behaviors of the agents in the simulations were modeled based on the workforce distribution statistics and assumptions on the daily activities of people:

Assumption 1. *Everyone uses the shortest path algorithm to get to their destination*

Assumption 2. *Most people will continue to use the road for leisure or errand matters after the office hours*

An example for the simulation on a typical day consists of people using the road network system for commutes to and from work, play, for work-related purposes under Assumption 1, running of errands and also for leisure under Assumption 2. Details on the behavior formulation can be found in this paper [27]. The data obtained from the simulations are traveled distances and time consumed on the roads by each vehicle and the average flow speed of each road segment on the network. Energy consumed by the vehicles is made up by two main components; the energy used in traveling the physical distance and the energy used to power all electrical components it has. Electrical components are lightings and other electrical parts that have a fixed energy consumption. The energy consumed for traveling is calculated as the required force to overcome the drag of the car in against air multiplied by the distance traveled. The Drag's force component [28] is given as:

$$F_D = \frac{1}{2}\rho v^2 C_D A \tag{1}$$

where F_D is the drag force component generated, ρ is the mass density of air, v is the velocity of the vehicle, C_D is the drag coefficient and A is the reference area of the vehicle going against air. Energy consumed is thus the product of distance traveled dt and drag force F_D.

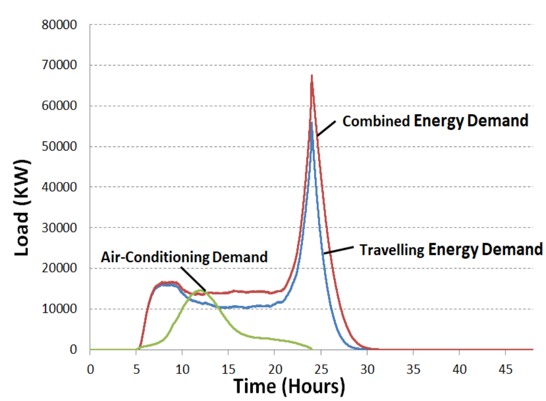

Fig. 4. Aggregated EV charging load distribution over 48 hours

Air-conditioning is more difficult to calculate compared to other electrical components. The energy consumed by it is dependent on the varying temperatures of the day. Hence, we developed and used a model simulating the air-conditioning system of a car. This potential energy is aggregated with the traveling load to form the total consumption [27] as shown in the Fig. 4 for all vehicles. The blue line represented the energy consumed while traveling on the road. The red line represent the traveling load while the green line is the combined traveling and air-conditioning load. Both lines are the expected load on the energy grid when the vehicle stops at its destination. This is a note-worthy observation as it informs the power generators that they do not need to abruptly increase their power generation to support this new load.

IV. Formulating the approach

Trading on the energy pool of Singapore occurs every 30 minutes. According to its market rules, the bids for energy trading will close 5 minutes before the end of every half hourly. If market clearing happens fast, then the new energy price is always given at the half hourly mark. Every energy retailer in Singapore would have 25 minutes to derive a new bid based on the new information for the next trade.

To formulate the above into an axiom, we use time interval between two trading events of i seconds and a closing time of c seconds exists before each trading event. We also assume that after the market is cleared and the latest clearing price is publicly available in u seconds. The total amount of time d for deriving the new bids can then be formulated as the remaining time d after deducting c and u.

There is a constraint that is to be satisfied; in order for the optimally computed bids to be submitted promptly, the time t for deriving the optimal trading bids must be within time d. Time t is a result of running the function of forecast technique σ with data size n. Therefore, n and σ determines time t.

In principle, forecast accuracy higher with more data. However, as said previously, computing time increases as the size of input data becomes larger. Moreover, the computing time is also affected by the learning method used. Therefore, we need to maximize the accuracy of each methods used while keeping to time limit d. And from the three methods, select the one that offers the best accurate forecast. The mathematic formulation of the above is given below in equation 2.

$$\begin{aligned} &\max_{0\leq n\leq\infty} f(\sigma, n) \leq d, \text{where} \\ &\sigma = \{LSTM, RNN, MLP\} \end{aligned} \tag{2}$$

V. Experiments

In this work, RNN, MLP and LSTM are the forecasting methods selected for study based on the literature review conducted and explained in section 2. LSTM is derived from RNN, but in the interest of this work, it would be good to find out if the added layer of improvement in LSTM is worth the additional time and resources in this scenario.

A. Experimental Setup

The charging load data is a non-continuous daily time series; consisting of 110 days worth in total. We separated the data into 3 groups, namely training, testing and verification data sets. It is divided in the ratio of 6:3:1 respectively; 60% training, 30% testing and the remaining 10% verification.

Part of the research is to investigate the effect of data size n on the computing time t. We tested the effect of data size on the time t by varying the amount of data from 1 to 47 days.

B. Programming language and hardware

The forecasting algorithms were developed and built in python. Libraries such as keras [16], tensorflow [17], pandas, numpy, statsmodels and etc were used. The hardware configurations that the forecasting algorithms were executed on are a 3.8 Ghz quad-core processor with a 6 MB cache, 8 GB memory and a NVIDIA GeForce GTX 1050Ti with 2GB GDDR5. The cuda library was invoked during tensorflow utilization to expedite the deep-learning process of the algorithms.

C. Settings for the learning networks

RNN, MLP and LSTM were programmed using Keras [16]. The base configurations for each network was used. There wasn't any optimization done on finding the best parameters that suited each learning network individually. Hence, tuned networks may incur additional time and skew the results. The learning function for all networks is based on root mean square error propagation as specified within Keras [16]. Likewise, the accuracy for all predictions is also based on root mean square function.

VI. Results

A. Computation Time Complexity

Tensorflow is able to make use of the CUDA library to accelerate the computation time required for training and forecasting with each model.

The computation time used by each learning network for training and testing can be seen in Fig. 5. It is interesting to note that LSTM as a variant of RNN required lesser computation time to process the same amount of data and also the computation time required to train the RNN model increases much faster compared to LSTM and MLP. This is due to the additional complexity incurred by bi-directional flow of information in the hidden layers of the RNN. The information flow in MLP is uni-directional, thus having lower complexity. LSTM has a "forget" capability that reduces the data processing required. Therefore, LSTM will always have a lower computation complexity compared to RNN. In comparing all three models, MLP required the least computation time compared to RNN and LSTM.

B. Accuracy

Besides being fast, there is also a need to be accurate. Fig. 6. shows the outcome of verifying the training data on itself. This is known as recall accuracy [29]. It can be seen that for recall MLP can be very bad at times. These are indicated by the peaks shown in Fig. 6. Possible reasons could be due MLP network not being able to fit data outliers in the training phase. Hence, when recalled with the same outliers, accuracy becomes bad.

Fig. 7. shows the results of using the trained models to provide the forecasts. Again, it can be seen that if data

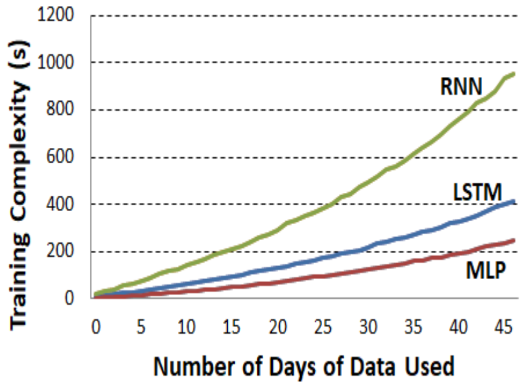

Fig. 5. Computation time required for LSTM, MLP and RNN according to the number of days of input training data

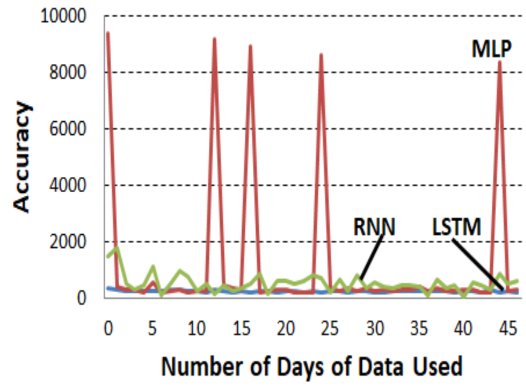

Fig. 6. Accuracy of learning network when tested against the training data itself

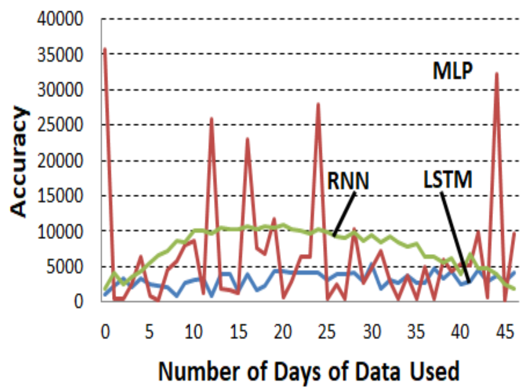

Fig. 7. Accuracy of learning network when tested on the test data

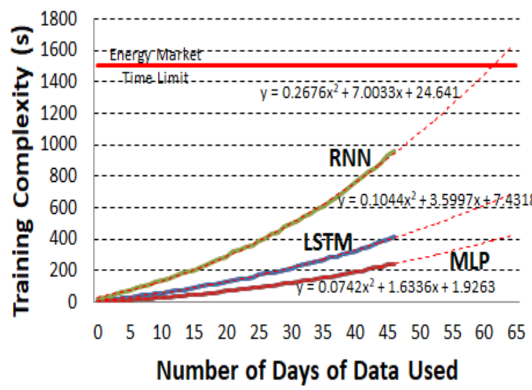

Fig. 8. Projection of maximal number of days for RNN to be infeasible for energy market trading

encountered is similar to those outliers in the training set, the accuracy will become bad. Although MLP is fast, it is not capable of maintaining consistency in terms of prediction variance. RNN is able maintain the consistency of prediction variance. RNN is better in this sense but its error rates are higher than that of LSTM, which appears to be the best model of these three.

At this point, it can be said that even with 47 days of data, the computation time will still be within the events' interval time. This is however based on Singapore's energy market context. We need to know when the models will become infeasible. It can be observed in Fig. 5. that amount of additional computation time required to train the learning model is increasing much faster for RNN than LSTM and MLP. By extrapolating Fig. 5 for all three models, it can be seen in Fig. 8. that RNN will become infeasible when training with 62 days of data. MLP and LSTM are still able to take in further amounts of data before themselves becoming infeasible to compute trade bids for Singapore's energy market; LSTM will become infeasible first followed by MLP.

It can be seen in Fig. 6. that LSTM has the best recall results followed by RNN and MLP. In Fig. 7, RNN seems to have better results when higher data amounts are used. If in the case where not that much data is available, RNN will not yield better results than LSTM. Therefore LSTM is able to work for low as well as high data amounts. In view of this, LSTM has the best consistent precision results followed by RNN and MLP. In terms of timing, MLP uses the least computation time for the same amount of data used across all the methods. LSTM came in at second whereas the limit of RNN is reached at 62 days of data point. However, MLP performs poorly in both the recall and precision results. Hence, therefore in terms accuracy and computation time, the deep learning method best suited for using real-time information of formulating energy trade bids for Singapore's Energy Market is LSTM.

This methodology is useful for people that needs to develop machine learning models for forecasting under time requirements. This methodology considers all constraints and tries to reduce and uniform their variables to a singular domain. For this paper, it was time. For example, using newly published market information and cut-off submission of the energy trading bids are all time constraints. In this comparison, we also see the performance of the three methods in the context of energy market information. The erratic precision performance of MLP was unexpected. RNN being unable to give good results when low data is used is also unexpected. Therefore, this served as a validation that LSTM still performed well in forecasting energy trading bids.

VII. Conclusion

This is the first study of using LSTM, MLP and RNN in forecasting electric vehicles' energy consumption. Furthermore, this was a study with the real world time limit of 25 minutes on computing time for forecasting the electric vehicles' further load. The time limit is based on Singapore's energy trading market. This is exactly the same amount of time that market participants have to determine the amount of energy to trade or sell. From Fig. 7. it is seen that LSTM has the best forecasting accuracy with thirteen days of data. The remaining methods requires at least twenty-five days of data for good results to be achieved. The advantage of LSTM here would be that it allows users to give the forecasting model a few runs to ensure the confidence of the forecast results.

In all the learning networks, the number of hidden layers and neurons assigned were not optimized. Therefore, for future works, the number of hidden layers and neurons for all three methods will be optimized for accuracy. This can be determined by repeating the training and test protocol illustrated in this paper with a fixed amount of data but varying the number of hidden layers and neurons for each iteration. The optimal data size that will produced the best accuracy was not determined in this paper and will also be considered for future works. From initiative results with regards to the precision of all three learning networks, it would seem that this search is heuristic in nature.

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