A Machine Learning Method for EV Range Prediction with Updates on Route Information and Traffic Conditions

Dohee Kim, Hong Gi Shim, Jeong Soo Eo

Automotive R&D Division, Hyundai Motor Group
150 Hyundaiyeonguso-ro, Namyang-eup
Hwaseong-si, Gyeonggi-do 18280, Korea
doheekim@hyundai.com

Abstract

Driver's anxiety about the remaining driving range of electric vehicles (EVs) has been quite improved by mounting a high-capacity battery pack. However, when EVs need to be charged, the drivers still feel uncomfortable if inaccurate range prediction is provided because the inaccuracy makes it difficult to decide when and where to charge EV. In this paper, to mitigate the EV range anxiety, a new machine learning (ML) method to enhance range prediction accuracy is proposed in a practical way. For continuously obtaining the recent traffic conditions ahead, input features indicating the near-future vehicle dynamics are connected to a long short-term memory (LSTM) network, which can consecutively utilize a relation of neighboring data, and then the output features of the LSTM network with another input features consisting of energy-related vehicle system states become another input layer for deep learning network (DNN). The proposed LSTM-DNN mixture model is trained by exploiting the driving data of about $160,000$ km and the following test performance shows that the model retains the range prediction accuracy of $2 \sim 3$ km in a time window of 40 min. The test results indicate that the LSTM-DNN range prediction model is able to make a far-sighted range prediction while considering varying map and traffic information to a destination.

Introduction

For internal combustion engine (ICE)-powered vehicles there are lots of gas stations throughout the country and the ICE vehicle owners can fill fuels easily and rapidly. However, easygoing refueling is a different story to electric vehicles since there is still a lack of charging stations and it takes a long time to charge. Concerns for EV charging schedule still make customers uneasy when considering purchasing an electric vehicle. A part of the concerns, generally known as range anxieties, has been quite improved and the recently released EVs can drive longer distances on a single full charge when compared to the initial stage of EV sales because car makers have extended the range by equipping their EVs with larger battery packages (Rauh, Franke, and Krems 2015; Viola 2021; Cheah 2021).

Even though the extended EV range decreases multiple errands for EV to find charging stations and accordingly decreases the number of feeling anxious for EV range, the range anxiety of whenever EV needs to be charged gets no better (Kollias and Gollapudi 2021; Rosenberg 2021). Before moving on to a destination, EV owners generally have to consider charging-related issues about the current battery state of charge (SOC), if there exist charging stations on the expected route, or if a battery charger is available in the destination, etc. There are two kinds of approaches to relax the charging-related concerns: building additional charging stations nationwide and providing accurate battery SOC and its driving range so that EV drivers are able to plan charging sensibly.

In general, the ordinary EVs display a metric related to the residual driving range named a distance to empty (DTE), remaining distance, remaining driving range, etc. The research for EV range prediction has been studied by considering physics-based modeling and test-based performance map (Ferreira, Monteiro, and Afonso 2013; Oliva, Weihrauch, and Bertram 2013; Miri, Fotouhi, and Ewin 2021) as well as by utilizing regression-based parameters estimation and machine learning techniques (Bi et al. 2018; Ondruska and Posner 2014; Fetene et al. 2017; Mao et al. 2021; Sun et al. 2019; Topic, Skugor, and Deur 2019; Warey et al. 2020; Zhao et al. 2020).

For predicting EV driving range, a particle filter with Markov chain is designed on the basis of the vehicle dynamics modeling, and the main parameters are determined by known driving cycle data sets (Oliva, Weihrauch, and Bertram 2013). In (Miri, Fotouhi, and Ewin 2021), a complex computer-based model that combines individual EV parts is developed for estimating the energy consumption and range prediction with several known driving cycles. Data-based modeling methods of (Bi, Wang, and Zhang 2018; Wang, Besselink, and Nijmeijer 2018) are employed to estimate the model parameters and (Fetene et al. 2017) provides meaningful analyses of big data to validate the factors affecting the energy consumption rate and the driving range of EVs.

To predict the residual range with ML methods, (Bi et al. 2018) and (Topic, Skugor, and Deur 2019) utilize RBF NN and CNN training respectively to mitigate the driver's range anxiety as one of the most pressing barriers adopting EVs (Noel et al. 2019). The ML methods in (Sun et al. 2019) and (Zhao et al. 2020) also show more accurate range prediction results than the multiple regression-based estimation methods, as illustrating several simulation comparison results. However, the method of (Sun et al. 2019) was validated by small numbers of sample data with only one-day length, and the method of (Zhao et al. 2020) shows a series of 10-sec preview range predictions, with somewhat a short prediction window to indicate the entire performance validation.

To lighten driver's range anxiety illustrated in Fig. 1, we propose an energy balance relation between vehicle-related signals and battery charging/discharging measurements. The energy relation is trained by utilizing a time-series data processing-based deep learning network. A LSTM network manages the time-series data to retain consecutive features of vehicle speed and acceleration materialized in aid of intelligent transportation system and navigation platform. With the output features resulting from the LSTM network, additional vehicle system states, which include the current battery SOC, auxiliary electric loads, and outdoor temperature, build another input structure connected to a deep neural network. As a consequent learning model, a LSTM-DNN mixture model is designed to train the energy balance relation to predict EV battery consumption energy, which is transformed into EV range prediction by considering the current available battery energy. To train the LSTM-DNN mixture model, one-year driving data sets during about 1000 hours, also expressed as about $160,000$ km were exploited, and to illustrate prediction performance the EV battery consumption energy and range prediction were evaluated every 40 min unit, which can be calibrated as a design parameter and considered to be a remaining trip time.

This study provides novelty in the following aspects:

- To practically achieve EV range prediction linked with predictive information regularly delivered from intelligent transportation system (ITS) and navigation platform, a novel two-stage input structure is designed for the proposed LSTM-DNN mixture model: in the first stage regarded as the LSTM network, the input structure has time-series profiles consisting of speed and acceleration updated by varying traffic conditions ahead, and with outputs of the LSTM network additional vehicle system signals are connected to the DNN as the second stage.
- By the LSTM network designed to capture long-term dynamics resulted in the speed and acceleration data, a far-sighted range prediction is achieved, and further the range prediction interval can be flexibly adjusted dependent on a residual trip time, since the LSTM-DNN mixture model retains a tailored structure to react exterior data with volatile traffic conditions.

The remainder of this paper is organized as follows: Section II describes an ITS-based ML method for EV range prediction. Section III specifies a LSTM-DNN mixture model for battery consumption energy prediction. Section IV presents data partition and the following performance analysis for the ML model. The key conclusions of the proposed ML method are summarized in Section V.

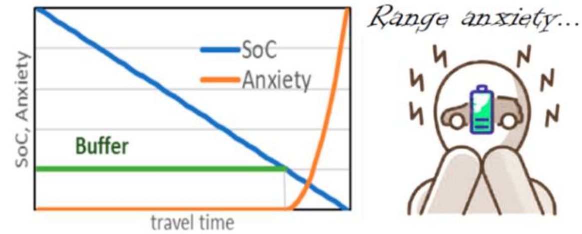

Figure 1: Illustrated descriptions for range anxiety, which starts to increase concerns when approaching a psychological limit of battery SOC (Viola 2021).

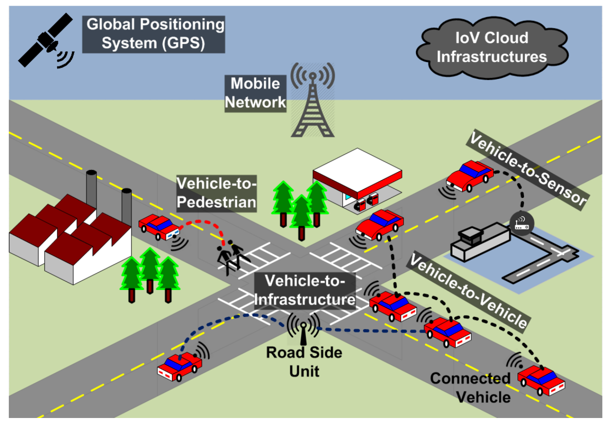

Figure 2: Illustrative representation of on-road communications in cloud infrastructure (Javed, Ben Hamida, and Znaidi 2016).

Toward Practical EV Range Prediction

Existing Methods and Utilization of Preview Information

Generally, the remaining driving range of EV has been estimated by employing various physics-based models and performance test data, which include physics-based vehicle energy consumption model, energy recuperation model by regenerative braking, energy consumption model by auxiliary electric devices and dual automatic temperature control, battery charging and discharging efficiency map, etc. However, these physics-based models do not consider nonlinear and uncertain state information, and moreover a way to simply combine the multiple physics-based models may frequently overlook complex dynamic states that cannot be ignored. To overcome the existing range prediction method, preview map and traffic information on the driving route can be interconnected to reasonably predict and update the battery energy consumption. As shown in Fig. 2, preview traffic information connected with navigation platforms can advise quantitative and qualitative traffic conditions on the remaining route to a destination.

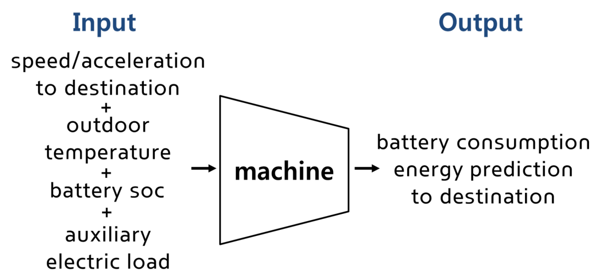

Figure 3: Conceptual representation of input and output structure for battery energy consumption prediction.

Machine Learning Model Based on Energy Balance Relation

By considering a relation of electric energy supply and mechanical energy demand, a data-driven ML model is proposed. EV has an energy balance relation, which consists of electric energy supply from battery package and mechanical energy demand by driving motor and other auxiliary electric devices, whereas recuperating or supplying mechanical energy by regenerative braking. The energy relation is simply expressed as

$$E_{Bat\_Consump} = E_{Driving} + E_{Non-Driving}, \tag{1}$$

where $E_{Bat\_Consump}$, $E_{Driving}$ and $E_{Non-Driving}$ are a battery consumption energy, driving-related and non-driving-related energy, respectively. Hence, utilizing big data going through various driving conditions such as road types, traffic congestion, temperatures, etc. can configure the energy relation-based learning model as shown in Fig. 3. Specifically, the energy relation is realized by a big data-based ML model where input signals, which comprise driving-related signals such as speed and acceleration and non-driving-related signals like battery state of charge, outdoor temperature, and auxiliary electric load, generate battery consumption energy through the ML model. The trained ML model plays a role as a prediction model that can yield battery consumption energy prediction once the input sets with the same structure are given. Therefore, with the battery consumption energy prediction denoted as $\hat{E}_{Bat\_Consump}$, the concluding range prediction is obtained from the following relation:

$$d_{Prd} = E_{Cur\_Bat} \times \frac{d_{Res}}{\hat{E}_{Bat\_Consump}}, \tag{2}$$

where d_{Prd} is a predicted EV range that can be transformed by the current available battery energy denoted as E_{Cur_Bat} as well as energy economy expressed as $d_{Res} \,/\, \hat{E}_{Bat\_Consump}$, where d_{Res} is a residual distance to a destination.

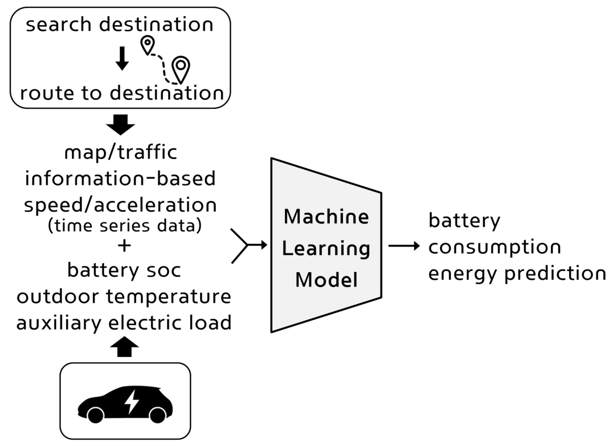

Figure 4: Schematic structure for battery consumption energy prediction to a destination based on preview route and traffic information.

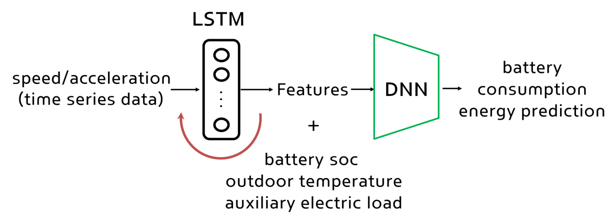

Figure 5: LSTM-DNN mixture model architecture and its conceptual signal flow.

Machine Learning Model for Battery Consumption Energy Prediction

Input and Output Structure to Train ML Model

On the given driving route determined by the navigation platform, the inputs and outputs of the ML model are configured to predict the near-future battery consumption energy by using the preview dynamics information and the current vehicle states. As shown in Fig. 4, the input consists of the preview dynamics information to be received by communication with the navigation platform and the battery-related vehicle states measured in real time, and the output is the battery consumption energy. The ML model of Fig. 4 trains the energy relation by using one-year data set, which was collected by driving Hyundai Kona EV during about $1000\,\text{hours}$, also denoted as about $160,000\,\text{km}$. The trained model linking with the inputs and output can update the predicted battery consumption energy with the current vehicle states once it regularly receives preview dynamics information from the navigation platform.

LSTM-DNN Mixture Model

The input data for the ML model is the preview dynamics information given from the current location to a destination and the vehicle states. The vehicle states consisting of SOC,

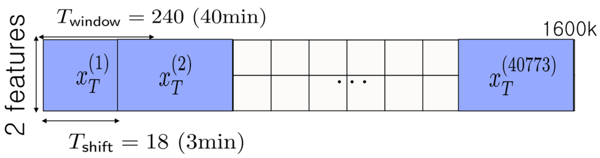

Figure 6: Signal structure and features of time series data as inputs for LSTM network.

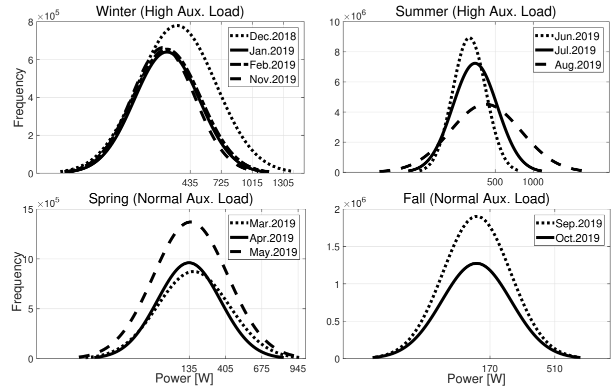

Figure 7: Seasonal histogram of non-driving loads comprising auxiliary electric devices, heat, ventilation, and air conditioning system: top-two histograms of winter and summer illustrate relatively high median values of non-driving power measured.

outdoor temperature, and non-driving load can affect the battery energy consumption with the respective state variations. However, when it comes to the speed and acceleration data, the information connected by order and continuity is quite critical since the speed and acceleration are time-related profiles. Hence, the ML model needs to be configured by a recurrent neural network (RNN), which can obtain feedback of the previous value within the loop while considering order and flow. Even though RNN has the merit to consecutively predict a relation of neighboring data, it is somewhat unstable to exploit long-term dependency that can retain characteristics of nonadjacent data. Therefore, a LSTM network is exploited to effectively predict the battery consumption energy as capturing long-term dynamics given by the speed and acceleration data to an endpoint. The resulting ML model is shown in Fig. 5. The LSTM network is trained by the time-series profiles comprising the speed and acceleration data to a destination. Then, with SOC, outdoor temperature and auxiliary electric load, the output features of the LSTM network make another input set for a deep neural network to predict the battery consumption energy. To effectively extract the consecutive features, the input data structures are designed in a window size of 40 min so that the features of the speed and acceleration profiles are extracted effectively, and the input window has a shifting size of $3\,\text{min}$ to represent a proper correlation between the adjacent data windows, as shown in Fig. 6. The number of the full time-series data arranged by the designed window and shifting size is 40773. Also, the input structure for the DNN has another three inputs with the same shifting size, as shown in Fig. 5. The outputs of the LSTM network, linked to the DNN, are determined by a number of neurons for the LSTM network, designed as 72. The output as a true label is the battery consumption energy computed in the same window size, which has the same shifting size as the input one.

Data Partition and Consequential Performance Analysis

Analysis of Non-driving Load Effects in Battery Energy Consumption

The EV battery consumption energy can be largely separated into driving energy and non-driving energy. The vehicle driving energy is mainly determined by the dynamics characteristics of the vehicle, and by the LSTM-based network learning which utilizes speed and acceleration data to a destination, the tendency of the battery energy consumption can be captured. However, the non-driving energy is generated from various causes such as auxiliary electric load, heat, ventilation, and air conditioning (HVAC), battery characteristics according to temperature, and dark energy hard to specify identities. It is difficult to model the respective disturbing elements, and further modeling the combined features is impractical. But the entire non-driving energy can be simply separated as

$$E_{Non-Driving} = E_{HVAC\_AUX} + E_{Dark}, \tag{3}$$

where E_{Dark} is an energy element negatively affecting range prediction, as consuming the battery energy inefficiently. Other than E_{HVAC_AUX} measured, E_{Dark} is a sum of energy dissipated by heats or battery efficiency characteristics. Also, E_{HVAC_AUX} displays obvious features according to each season, as shown in Fig. 7 where summer and winter experience higher auxiliary energy than spring and fall. Therefore, to illustrate a ratio of total driving distance divided by total battery consumption energy, distance driven per battery energy consumption (DPB) index is defined as

$$DPB_i = \frac{D_{Tot_i}}{E_{Tot\_Bat\_Consump_i}}, \tag{4}$$

where D_{Tot_i} is a total driving distance, $E_{Tot\_Bat\_Consump_i}$ is a total battery consumption energy and i is denoted as a specified month. Fig. 8 shows that Nov., Jan, Feb. and Mar. indicating winter have less DPB_i. Also, to identify a ratio of total auxiliary electric energy divided by total battery consumption energy, auxiliary electric energy per battery energy (AUXPB) index is defined as

$$AUXPB_i = \frac{E_{Tot\_HVAC\_AUX_i}}{E_{Tot\_Bat\_Consump_i}}. \tag{5}$$

Fig. 9 illustrates that the auxiliary energy is quite consumed by heating and warm-up in winter. Furthermore, to examine only the effects of how the battery consumption energy influences the EV range, distance driven per driving energy

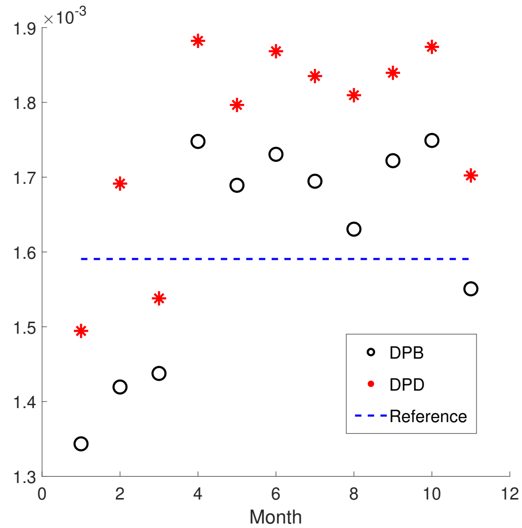

Figure 8: Monthly distribution of DPB and DPD indexes with a reference line separating normal and high non-driving load data.

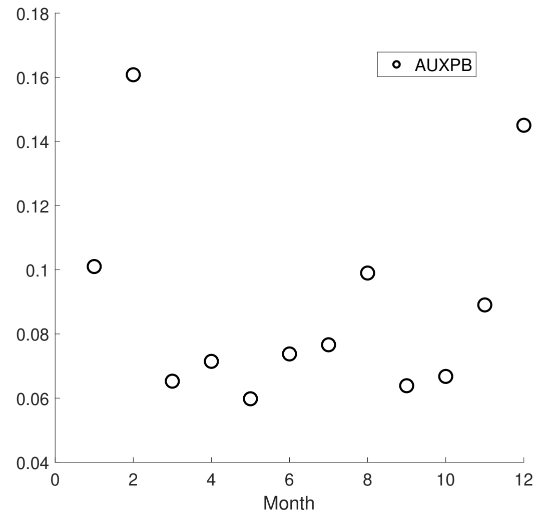

Figure 9: Monthly distribution of AUXPB index during one year.

consumption (DPD) index, excluding the auxiliary energy from the battery consumption energy, is defined as

$$DPD_i = \frac{D_{Tot_i}}{E_{Tot\_Bat\_Consump_i} - E_{Tot\_HVAC\_AUX_i}}. \quad (6)$$

$E_{Tot\_HVAC\_AUX_i}$ is total auxiliary energy. DPD_i of Fig. 8 shows that Aug. excluding cooling energy appears to be increased in the aspect of the range efficiency, but the season with a low temperature indicates low growths in the range efficiency, even if the auxiliary energy being made up of heating or warm-up is excluded. The reasons can be inferred that the driving in the low temperature experienced low energy efficiency resulting from chemical characteristics of battery cells and accordingly the low energy efficiency provided negative effects to the range efficiency. Hence, separating the data set by DPB index and training the model by the respective data sets would be able to offer more accurate battery consumption prediction.

Performance Analysis of ML Models Trained by Separated Data Sets

As shown in Fig. 8, one-year data set is separated into the normal load (NL) and high load (HL) data sets by the reference line of DPB index. Therefore the respective three data sets are exploited to individually train the LSTM-DNN mixture model: one is a full data set of one year, another is a NL data set above the reference line, and the other is a HL data set below the reference line. To equivalently compare the three trained models, each model holds the same training conditions, which include one LSTM layer with 72 neurons, 40 epochs, regularization parameter of 0.001, the same schedule of learning rate decay, etc. In Fig. 10, the loss values denoted as mean absolute errors converge to a stable area with increasing epoch, as one complete pass of the training data. All three LSTM-DNN mixture models were trained so that each model is settled at each stable steady-state, and the detailed performance results are listed as Table 1 and the error metric is a normalized root mean squared error (NRMSE) specified as

$$NRMSE := \frac{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)} - \hat{y}^{(i)}\right)^2}}{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)} - y_{mean}\right)^2}}. \quad (7)$$

	Full	Normal	High
$NRMSE_{Train}$	0.054	0.050	0.046
$NRMSE_{Val}$	0.055	0.051	0.048

Table 1: Comparison of training and validation NRMSE for three data sets.

Regarding the respective training and validation data sets for all three models, the NRMSE values indicate well-trained results without overfitting, and the prediction test results using the trained models embody the EV range prediction performance: for three types of examples with only a single range prediction per 40 min time window, the medians of errors between ground truth and predicted values are 2.67 km (in 4068 examples of Full data), 2.23 km (in 2415 examples of NL data) and 1.72 km (in 1653 examples of HL data), respectively. Furthermore, to inspect the model performance resulting from the data separation, the full data-trained and NL data-trained models are evaluated by the NL data set, respectively. As shown in Table 2 and Fig. 11, the NL data-trained model as a customized one shows better performance of 5.2 % than the full data-trained model as a general-purpose one. Similarly, the full data-trained and HL data-trained models are evaluated by the HL data set,

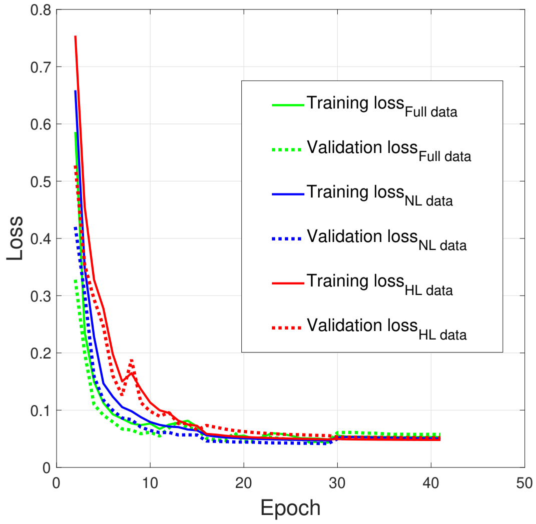

Figure 10: Training and validation loss history during 40 epochs regarding full data, NL data and HL data.

Data type	NL Data		HL Data	
Model	Full	Nor	Full	HL
Range error [km]	2.35	2.23	1.83	1.72

Table 2: Comparison of range prediction results: range prediction errors in NL and HL test data set.

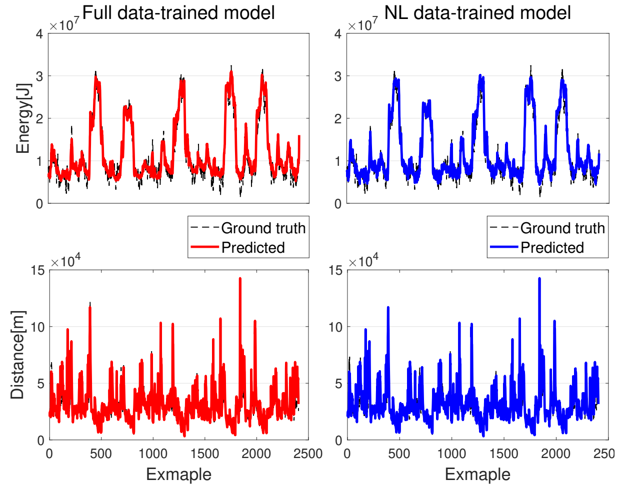

Figure 11: Comparison results of full data-trained model and NL data-trained model evaluating NL test data set.

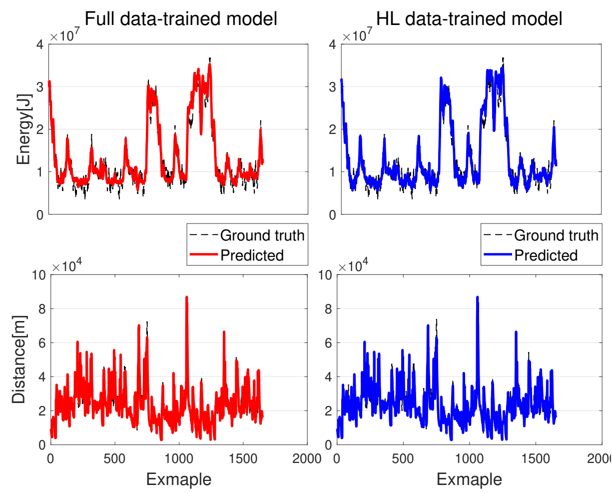

Figure 12: Comparison results of full data-trained model and HL data-trained model evaluating HL test data set.

respectively. In Table 2 and Fig. 12, the HL data-trained model shows enhanced results by $6.8\ \%$ compared to the full data-trained model. Compared to other methods of (Sun et al. 2019; Zhao et al. 2020), which predict the remaining distance of EV by using ML methods, the illustrated performance results show that the proposed LSTM-DNN mixture model can predict the EV remaining range much further while using the less number of input features. Besides, the proposed method, which can update the EV range prediction regarding the entire range of residual time and distance throughout the given route, raises expectations to alleviate the EV range anxiety, because reflecting realistic information aligned with the look-ahead traffic conditions displayed in the vehicle infotainment system.

Conclusions

A new ML method to achieve the improved EV range prediction is proposed by merging the benefits of each LSTM network and DNN. The LSTM network retains the long-term dynamics established by the look-ahead speed and acceleration information consecutively updated from ITS and navigation system, while the DNN builds a nonlinear network model to concretize input and output energy balance relation. To train the LSTM-DNN mixture model, Hyundai Kona EV driving data during about 1000 hours, also denoted as about $160,000$ km are employed. Considering the DPB index to indicate distance per battery consumption energy, the full data set is separated into the normal and high load data sets. The three LSTM-DNN mixture models were trained individually by the respective three data sets, and with a series of test processes for performance verification, the LSTM-DNN mixture models show well-trained performance as well as the system states converged to stable regions. The test results indicate that the LSTM-DNN model possesses an ability to practically improve the EV range prediction in connection with the ITS and navigation platforms. To further verify the reliable performance linked with ITS-based information, the LSTM-DNN model needs to be implemented to in-vehicle control boards or an embedded computer system. Also, a continual learning method for the LSTM-DNN model would be one of durable solutions to keep the EV range prediction performance against battery aging.

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