Driver-Adaptive Real-Time Range Estimation for Electric Vehicles in Dynamic Traffic Conditions

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***Abstract*—Electric Vehicles (EVs) are becoming a highly regarded way of curtailing greenhouse gas emissions, as well as attaining energy efficiency in general in the present transportation system. In spite of these pros, the possibility of estimating the remaining driving range reliably also is a critical technical challenge, especially when operating under the actual conditions encountered in the real world. Different levels of traffic density, road nature, and environmental factors, as well as distinctive personalized driving behavior, pose nonlinear and time sensitive factors that do not well reflect on the traditional state of charge-based estimation procedures. As a solution to such shortcomings, the paper proposes a driver adaptive and real-time EV range estimation system, using a hybrid deep learning framework. The offered solution combines a Multilayer Perceptron (MLP) network and a Long Short-Term Memory (LSTM) network to combine dynamics and long-term behavioral patterns of vehicles into a single model. The MLP part is concerned with the instant parameters like vehicle speed, acceleration, and battery state of charge whereas the LSTM part contains temporal dependencies related to the behavior in past and road nature. The system achieves a customized and constantly upgraded range forecast by utilizing the results of the two models. The suggested structure will be implemented as an offline execution on embedded vehicle equipment, allowing it to run with low latency and offer greater reliability independent of being connected to a cloud. The experimental analysis performed in various operating driving conditions proves that the suggested process can be more accurate and robust in its prediction results than the conventional approaches to e-commerce SOC and independent machine learning models. The better estimation results are causing the lowered range anxiety, in addition to the increased driver trust, which enables more confident and accurate plan of trips by the electric vehicle operators.**

***Index Terms*—Electric Vehicle, Range Estimation, Driver Behavior Modeling, Deep Learning, MLP, LSTM**

I. INTRODUCTION

Lack of sustainability in mobility has been a matter of concern because the transportation industry is a demonstration of significant energy use and emitting greenhouse gas emissions as a cause of global energy consumption. EVs are poised to become an alternative that is very promising compared to regular vehicles based on the internal combustion engine because of the higher efficiency of their energy, no emission of tailpipes, and the possibility of combining with renewable energy sources [1]. Consequently, EVs are now more likely to be considered an important part of the transportation systems in the future. But in spite of all these benefits, the popularity of EVs is yet to be significantly increased due to the problem of the reliability of driving range. The range anxiety, which can be described as the uncertainty related to the remaining range of the travel before the battery runs out, is still a major issue to EV users [2]. Relevant and reliable estimation of the range is thus a must to enhance the confidence of drivers and also aid the planning of trips. Traditional models of estimating EV range mainly rely on models of battery state of charge (SOC) and models of average energy consumption. Although they are computationally efficient, these techniques do not represent the nonlinear and dynamic feedback induced by the reality of driving environment such as traffic congestion, road properties, environmental problems and battery aging [6], [7]. This causes the predicted ranges of driving to have deviations with the actual vehicle performance.

According to recent research, driver behavior is more critical to add to range estimation models. The differences in the driving style that includes driving acceleration level and braking patterns have a considerable impact on the energy consumption despite similar conditions of operation [4]. These complicated relationships have been modeled using machine learning models such as multilayer perceptron and recurrent neural networks, and hybrid MLP based-LSTM models have been shown to exhibit better prediction accuracy due to the integration of the short and long-term vehicle dynamics and behavioral patterns [3], [5], [9]. Nevertheless, the majority of existing machine learning-driven solutions are cloud-based the processing, which is associated with latency, connectivity requirement, and privacy issues [8]. To overcome these drawbacks, the current paper suggests a driver-adaptive, real-time EV range estimation frame work that is implemented as an offline hybrid MLP-LSTM model that can be run on embedded devices and provide precise and individual range estimates under real world driving condition.

II. BACKGROUNDANDMOTIVATION

The remaining driving range of electric vehicles is a complicated issue of accurate estimation as it highly depends on the behavior of the battery, the dynamics of the vehicle and the operating circumstances. Lithium-ion batteries which are often employed in EVs are nonlinear and they depend on characteristics like temperature, internal resistance, depth of discharge, charging history as well as ageing impacts [1], [6]. These differences influence the energy accessible and the pace, at which energy is supplied to the vehicle in the course of its operation, and the estimation of range is excessively doubtful in real-life situations. Besides battery related considerations, vehicle level dynamics are also crucial in energy consumption determination. The speed, acceleration, road gradient, aerodynamic drag, and rolling resistance are power demand parameters that are affected by significant parameter variations [7]. Driving conditions enhance the variability; e.g.in city areas due to stop and go traffic, there are a lot of moments of acceleration and braking whereas in highways driving, there is a constant high-speed leading to greater losses to aerodynamism. Other systems such as air conditioning and heating are also a contributor to other energy usage, especially during extreme weather conditions [2], [6]. The driver also leads to another significant source of uncertainty in the estimation of EV range. Research has demonstrated that such characteristics of acceleration as aggression, sudden jolts, and unstable speed regulation may cause significantly increased energy consumption in contrast with the abilities to drive consistently and steadily [4].

As an individual driving a bit even under the same conditions of operation in terms of route and other environmental factors, the same vehicle when driving the same route can have apparent difference in the energy consumption pattern. The traditional range estimation methods do not largely take into consideration such customized driving features and the predictions made tend to be generic and therefore may not apply to the real driving behavior [5]. Recent studies have also examined machine learning-based solutions to these problems by training complex relations among vehicle conditions, driving and energy use [3], [8]. Although multilayer perceptron are useful in the modeling of instantaneous nonlinear dynamics, they are not very good in describing the temporal dependencies. Recurrent neural networks (especially the Long Short-Term memory (LSTM) models) have been more successful in modeling long-term behavioral and route-intensive tendencies [9], [10].

However many of these deployed designs depend on cloud processing, which adds a latency and connectivity limits as well as privacy risks. A combination of short-term and long-term modeling capabilities with the desire to run in real time on embedded devices drives these elimitations, which prompts the creation of an offline, driver-adaptive range estimation model.

III. LITERATURE SURVEY

Over the past decade, people have tried everything to as certain how much power electric vehicles use and their range. They also observe how a vehicle will travel and how the battery will perform and what is actually taking place on the roadway like rolling friction, air drag, hills and the amount of energy utilized in the drive train. The models are more or less explainable of what is going on under the hood however, under extraordinarily thin conditions, and they fail miserably when the traffic is not acting itself straight and the drivers are not either [1][7]. The machine learning methods and the statistical methods then emerged with the aim of stitching some of them. These models are used to learn the driving data of the past and present it using different types of regression, decision trees, support vectors machine, etc. They tend to perform better in determining the energy consumption, and poorly in determining changes as time progresses, and this is not very good at all in cases in which the driving conditions change [4][6]. Multilayer perceptron (MLP) could be regarded as man-made neural networks that do their best in tangling all those complicated, nonlinear systems of connections between what the car is doing and what is outside.

Their service in short-time predictions that it is worthwhile making on the spur of the moment, but since they lack intelligence in the reading sequences, they perform abysmal performances when you have to predict with energy or gain in a wider distance length [3][8]. The aspect of time had to be dealt with by researchers in LSTM networks. LSTMs are sequence data models and can therefore be employed to monitor how a driving behavior and an energy consumption evolves with time. They are more inclined towards making predictions of the greater trips which are more certain as far as ranges are concerned [9][10]. Recently, people started to make problems interchangeable, mixing MLPs and LSTMs with physics-based models with machine learning. These ambivalent constructions do aim at accomplishing the best of both and theoretically, they are the constructions that support prediction sand make them much more solid. Oh, they are not quite devoid of their ills. They would be pure heavy calculation wise, difficult to fit in real cars and can hardly conform to new drivers. Therefore, the gap exists and this is where the present study fits in. It attempts to fabricate something one and operates in real time and responsive to whoever has the wheel [3][5][10].

IV. SYSTEMOVERVIEW/ARCHITECTURE

It's just a combination of this smart driver-centric setup which calculates your EV range on the road [1]. In other words, it does not simply use a single thing but drags everything, including your long-term habits of driving [9]. Such combination is indeed useful in getting better estimates of range [3]. It has a sensor configuration that captures data such as battery level of charge, speed, intensity of hitting he gas and your position, and even consumption of power of appliances such as the AC [7]. Occasionally it may even scrutinize that stuff such as hills, traffic, or the outside temperature, just to have a better knack on the actual situation with your energy [6]. Not all systems do all that every time but the elastic ones do [10]. After it has received all that raw data, the second thing is to clean it. They rationalize numbers to get them all fitting in, drop the noisy bits, patch any holes that arise, and put their attention on what really counts in the amount of energy you are burning [6]. This prevents the possibility of the model not functioning [8]. The fore castings action is rather entertaining-it is a hybrid engine. It learns with an MLP network to identify the nonlinear and difficult correlations between what is happening to the car and the amount of power it is consuming at a given moment in time [3]. Next, there is an LSTM network, which considers the longer-term trends, and manages to extract the way you tend to drive, your habits even the routes, which you take [9]. Both these models are injected in to a weighted layer that averages out short term variations and larger trends hence your range estimate moves with you [5].

This combination of models makes the entire thing very bendable, which is gigantic, as conditions in which one is driving are never the same [10]. The system also speaks to the driver via dashboards, visual effect and in other cases just by alerts like this: Lights or sounds when your range is getting low [2]. That partially relieves the anxiety of not knowing whether you will arrive at your destination, and it assists in planning the trips [1]. All is modular and hence scales easily as it is fast canal so work even off-line, it is great to straighten it up into real cars [8]. Ultimately, it integrates real-time driving information, your behavioral pattern with the time as well as how much you contribute as a driver [4]. I might have been rubbing a few of the knottier links, but that is the thing it is a good foundation in which to grant range to drivers estimates which in fact are not comparable with their driving [3], [9].

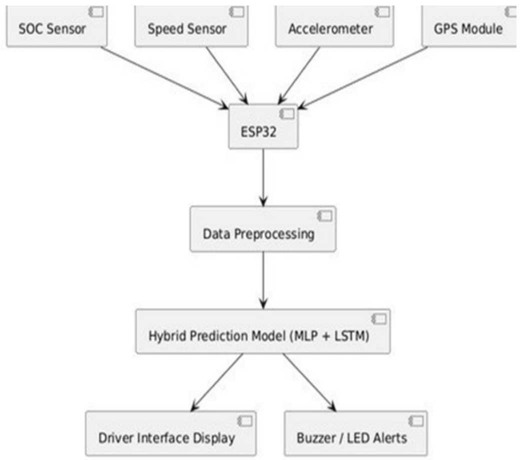

Fig.1 systematic block diagram

V. METHODOLOGY

Instantaneous data gathering, processing, hybrid deep learning and embedded implementation include the whole setup for this system [8]. It aims at estimating range in a manner which adapts itself to the manner of the driver starts with collecting raw data of sensor like speed of the EV, GPS positioning, acceleration and other helper modules [7]. Next step is preprocessing. They in effect purge the data, eliminate noise, and make sures that nothing is out of proportion [6]. Then they focus on the overhangs that count in energy consumption stuff defining the real car eats up [4]. Then, there is this temporal encoding step. It looks at how things change with time, acquires dependencies and scouts up on habits in driving procedure [9].

So, the model doesn't just respond to the current situation, it knows how things build up during a trip. That's pretty important for to make the prediction close [10]. On the modeling aspect, they apply an MLP network to process all the short-term nonlinear links such as the effect of the setting of a vehicle and the environment influence energy consumption[3].Then there is the LSTM that explores the far greater stuff: here is how you drive and how you drive the road across a sequence[9].That was the thing that allowed the system to read just. Each driver's style [5]. Ultimately, they synthesize the results, then weighted linear cycles of both of these networks to obtain the ultimate range prediction [3], [5]. This forecast continues updating at real time, sliding windows or live data feeds basing on these lives [10]. They also have got an alarm system. If your range starts you dip too low it will tell you and prevent your battery failure of a stuck car [2]. The whole setup is made to remain lean, and their four runs on embedded hardware, even out of the net, and does not stall when you are actually driving [8]. They apply measures such as RMSE, MAE and to determine whether it is working realism, and try it out under every sort of driving condition [6], [7]. That way, they ensure that it actually provides effective and customized EV range estimates [3], [9]. There are certain overlaps--such as that which the data flows inside the system-but in consequence it is a pretty one tight process.

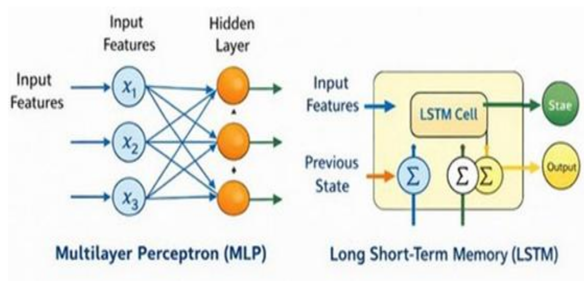

Fig.2 mlp & Lstm

VI. RESULTSANDANALYSIS

The proposed hybrid MLP LSTM range estimation frame work is tested and exposed to different driving situations with both urban and suburban and highway conditions. They test the changes in driving, traffic density used in cases, environment, and behavior in cases of real- world vehicle operation [2], [7]. The evaluation focuses on evaluating robustness, accuracy of prediction and real-time feasibility.

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) is used to measure prediction performance. Compared to traditional SOC-based and single machine approaches the proposed approach help store alise a reduction in learning models in RMSE of about 15% - 20%, which is better precision of dynamics of nonlinear and time-varying energy consumption patterns [3], [6].

The formula for RMSE and MSE is given as

$$\textbf{Formula: } RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$\textbf{Formula: } MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

The inclusion of driver behavior with an additional boost by the LSTM part reliability of prediction among various styles of driving.[9]. Besides the accuracy improvement aspect, the proposed system will have an addition of improvement - low computational latency which makes it appropriate to deploy real-time embedded. The offline operation caters to the needs of cloud connectivity elimination, enhancing system reliability and data privacy [8]. Overall, the results justify the success of the hybrid solution suggested to estimate practical range of EV.

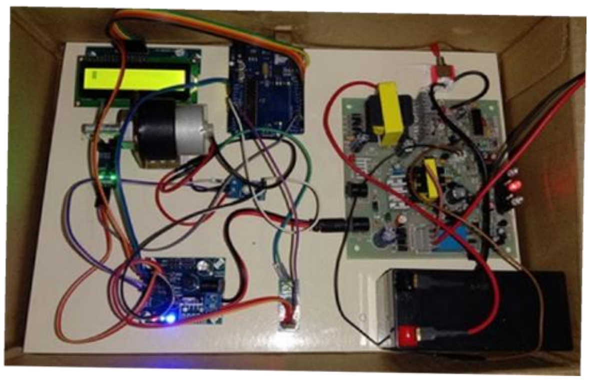

Fig.3 hardware kit result

Fig.4 final setup

VII. FUTURE SCOPE

Further studies can be devoted to the enhancement of the generalization capacity of the suggested range estimation model by increasing the dataset size to provide more diverse variety of vehicle, battery chemistries, driving conditions, climatic, and models. Work with the data of various geographical areas and traffic patterns would enable the model to become better adjusted to various real-world situations. In addition, the inclusion of additional sensor data, e.g. battery temperature, road gradient, auxiliary and regenerative braking efficiency. It could further increase the accuracy system power consumption of modeling and prediction of energy consumption [6], [7]. The other sustainability option is the implementation of adaptive and incremental learning plans which allow the model to change through causes of driving and vehicle specifications evolve over time. Edge cloud hybrid architecture can be used to learn, be searched to justify the regular model refinement and enforcing the offline operation in real time with critical range estimation tasks [8]. In addition, model compression and different methods of minimizing could be explored maximization also computational overhead and enable deployment on low-power embedded platforms. Application of the suggested framework beautiful navigation and route planning systems can also be used. Also, improve active energy-conscious decision-making performance and general driving effectiveness [10].

VIII. CONCLUSION

The current paper discussed a driver adaptive real-time electric vehicle range estimations chemeon hybrid Multilayer, Long Short-Term Memory deep learning and Perceptron architecture. The offered strategy incorporates the immediate long-term driving behavior to produce dynamics of vehicles specific range projections that are closer to the actual operating world conditions. It can utilize the short-term and temporal features, the system deals with major constraints of traditional SOC- based estimation algorithms and independent machine learning models [3], [5]. Experimental testing in different driving cases shows that the suggested framework brings superior accuracy in prediction, lesser error of estimation and improved stability in different driving patterns and conditions. At the offline execution endures low latency, enhanced credibility and increased data confidentiality which makes the system that fits into the embedded deployment. All in all, the offered methodology has a beneficial impact on the minimization range anxiety and helps to have apt energy management of electric cars and thus advance more user trust and helping to spread EV technology [1], [2].

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