Hybrid Deep Learning Mechanism for Charging Control and Management of Electric Vehicles

Ashwin Kavasseri Venkitaraman and Venkata Satya Rahul Kosuru

***Abstract* — In perspective of their environmental friendliness and energy efficiency, Electric Vehicles (EVs) are posing a threat to traditional gasoline automobiles. Identifying the future charging needs of EV users may be aided by the forecasting of states linked to EV charging. It might deliver customized charge capacity statistics based on users' real-time locations as well as direct the operation and management of charging infrastructure. Consequently, an emergent problem is the effective model of EV charging state predictions. In this study, a hybrid deep learning approach is suggested to assure safe and dependable charging operations that prevent the battery from being overcharged or discharged. A Recursive Neural Networks (RNNs) for feature extraction process is suggested to acquire adequate feature information on the battery. The bidirectional gated recurrent unit framework (GRU) was then established by the study to predict the state of the EV. The GRU receives its input from the RNNs' output, which substantially enhances the effectiveness of the model. Because of its much simpler structure, the RNN-GRU has a lower computational performance. The experimental findings demonstrate the GRU method's ability to accurately track mileage of the electric vehicle. A hybrid deep learning-based prediction approach could give quick convergence speed less error rate in comparison to the appropriate method for obtaining state of charge estimate over conventional models, as demonstrated by the extensive real-world tests.**

***Keywords* — Charge Control, Electric Vehicle, Gated Recurrent Units (GRU), Hybrid Deep Learning (HDL), Recursive Neural Network (RNN).**

I. Introduction

Lately, both environmental degradation and energy shortages have gotten increased attention. The effect of increased vehicle exhaust emissions necessitates an acceleration of the energy revolution in the automobile sector. Electric vehicles (EVs) provide a number of advantages over conventional vehicles, including the ability to conserve energy, emit fewer pollutants, and rely less on fossil fuels. Their progress has been greatly expedited by this. The power supply system is the key element of an electric vehicle (EV), and it has a big impact on how well the car runs as a whole. The problem with electric vehicles' power supply now prevents them from developing to their full potential [1]. The attempts to address difficulties with renewable sources and ecological sustainability depend heavily on electric vehicles (EVs) [2]. Unlike any other EV technology, battery capacity is what determines the car's performance as well as range. Despite significant advancements in batteries over the past several years, the enormous spikes have been the major issue in diminishing battery service life, a situation that is common in EVs because of traffic, roads, as well as driving style [3]. In view of concerns about serious environmental and resource shortage challenges, reducing the combustion efficiency of pollutants is a significant and challenging topic in the transportation business [4]. Conventional electric vehicle energy storage systems make use of battery-based storage units that have a number of restrictions and downsides [5]. First, the battery's poor energy density prevents it from providing the full amount of power needed by EVs during acceleration or ascent. Even having more battery cells could provide the necessary power; the EV volume would increase dramatically. Frequent current changes in battery energy storage systems also result in increased heat output and reduced battery life. To be promoted and utilized more widely, electric vehicles need to have more precise energy, more specific performance, a longer lifespan of the battery storage system, with greater recharging efficiency [6].

By utilizing a modest charging station, extended-range electric vehicles (EREV), might effectively address the issue of the relatively short driving range of EVs. A battery serves as the EREV's primary energy source with a smaller range-extension device that includes an engine generating unit, serves as its secondary energy source. Within a set number of miles, the battery gives the vehicle all of its available power, reducing emissions [7]. The battery could maintain the automobile operating until its state of charge (SOC) falls below the minimum level. The range extender then extends the trip even further by supplying more power to the engine. The hybrid electric vehicle (HEV) known as an electric range extender uses a battery as its main power source. Small greenhouse gas benefits result from this. Additionally, the EREV could have minimum environmental impact even though it has a long driving range when fuel cell technology is available to substitute the engine-generator series as the replaceable battery [8], low energy usage is another benefit, and EV research has recently covered this issue as well. It is crucial to have a thorough grasp of the battery capacity including charging parameters before modeling an EV load for system studies. To achieve the legal criteria for the quality of the charging power and volt and that is important to build EV battery chargers with appropriate charging algorithms.

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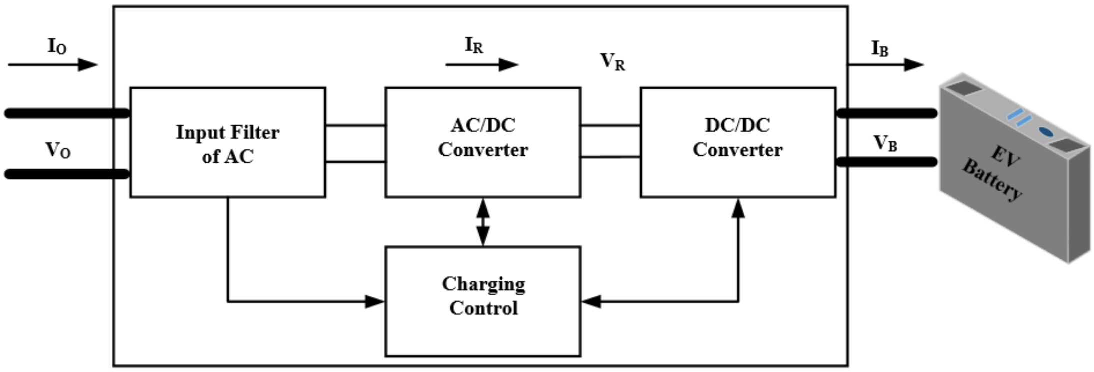

Fig. 1. Basic Battery charger for EV.

Every one of the chargers on the market right now uses unidirectional chargers, and the conventional ways of charging are constant current (CC) and constant voltage (CV). A basic block diagram of an electric vehicle (EV) on-board battery charger can be found in Fig. 1. It shows multiple converters: an isolated DC-DC converter with both input and output electromagnetic interference (EMI) filters, accompanied by an isolated AC-DC converter with Power Factor Correction (PFC) [9].

In this case, the batteries regularly have to provide quick power needs during acceleration and deceleration. The batteries require a greater proportion of capacity if they are to respond to such fluctuations quickly. Despite being an option, higher rate batteries are often more costly than their lower rate counterparts. They are typically bigger as well. Furthermore, the capacity property of a battery is usually used to predict how long a battery would last following repeated charge and discharge processes. It is widely accepted that if a battery's maximum throughput is much less than 80% of its maximum load, it would not be acceptable to be used in applications for electric vehicles [10]. Since it is unable to test the battery's actual capabilities, estimations of the model's parameters are often produced utilizing methods including progressive performance assessment and radial basis functions networking [11]. Even if the capacity forecast might be utilized to optimize the battery's recharging schedules, peak usages are still unavoidable under high-power load scenarios. The overcharging voltage would generate a lot of heating within the battery as a consequence of the ohmic resistance value's peculiar reactions, which would quickly degrade the battery's capacity or maybe result in the collapse of the complete system [12].

In an electric car, the batteries management system (BMS) primarily makes ensuring that the battery is operating safely. The BMS plays a crucial role in emerging electrified vehicle technologies because it monitors battery conditions and ensures the batteries are used safely. Among the most crucial phases of the BMS is the state of charge (SOC) [13]. The SOC is essential data to enhance performance and prolong battery life. A wide range of techniques have been suggested for precise SOC estimation. The simplest method is to count in ampere-hours (Ah). However, the accumulation of startup as well as current sensing mistakes causes the Ah counting to drift. The open circuit voltage (OCV) is another logical way to calculate SOC. The load and OCV must be disconnected for this approach to work, and it can only be measured after the battery has had a long rest. As a result, it makes it more urgent to examine other SOC estimating methods. A neural network that uses a hierarchical idea system is able to comprehend complicated behaviour and know from experience. As a result, the state observers utilizing the neural network structure have attracted a lot of attention lately. Comparing the neural network-based SOC estimating technique to other SOC estimation methods like Ah counting and the OCV, it has demonstrated exceptional performance [14].

How to effectively build and maintain charging facilities is one of the challenges for EV promotion. Electric Vehicle and plug-in hybrid EV customers must recharge electricity energy more often than GV users because of the short driving range with a long time. They like to charge their electric vehicles without taking major diversions from their usual paths. Therefore, it is important to give EV users' travel patterns and charging habits considerably more thought while operating charging stations [15]. Here, the terms “travelling behaviour” and “charging pattern” refer to the dynamic changes in an EV's travelling and charging states over time and space. Operators worry about a potential overload of the energy grid brought on by a massive amount of EVs charging at once [16]. The operators might anticipate various charging demand categories in the upcoming few hours also take the appropriate management measures in advance if they were able to estimate EV states for a plausible situation. Based on their past charging behaviour, we can also predict the next charging time and kind for users. It's important to note that the term charging state used is inclusive of both the discharging and charging processes.

To forecast EV states, a data-driven system using hybrid deep learning is proposed. Because other situations, like lower battery, also indicate the latent charging behaviour, the investigation begins by extracting the battery attributes rather than immediately predicting the charging demand. More information is provided by the charging-related states as a whole than just the charging activity. Additionally, the time allotted to each distinct condition could reveal the time-usage pattern of an EV, particularly the distinct time intervals for “outside charging” and “indoor charging”, which may suggest various kinds of loads on the electric grid. A Recursive Neural Networks (RNNs) approach is used for feature extraction process, which gets adequate feature information on the battery. The team then built the bidirectional gated recurrent unit framework (GRU) to forecast the state of the EV. The outcome of the RNNs serves as the input for the GRU, which significantly improves the model's performance. The RNN-GRU performs less computationally due to its significantly simpler structure. The experimental results show that variations in electric car mileage may be accurately tracked using the GRU approach. As shown by the extensive real-world tests, a hybrid deep learning-based prediction approach may offer quick convergence speed in comparison to the proper approach for producing SOC estimate over conventional models.

The following Section II discusses the Literature review of the study. The problem statement of the study is given in Section III. In Section IV, the proposed methodology is briefly explained. The prediction and Estimation are given in Sections V and VI. Result of the proposed approach is in Section VII with Tables and Graphs. Finally, the study is concluded in Section VIII.

II. Related Works

Electric vehicles (EVs) and battery technology improvement have both attracted a lot of attention recently. EV power usage still requires more energy than the existing battery supply can provide, despite significant advancements in battery technology. Non-monotonic energy usage that is followed by swift changes as the battery is drained is one of the key issues. This has a significant negative impact on the battery's electrochemical reaction. The battery can be used in conjunction with a super capacitor, which is essentially an electrochemical method with the same architecture but with a higher rate capability and improved cyclability. When the battery is unable to provide the additional energy needed in this configuration, the super capacitor may. In contrast to the battery as well as the super capacitor as individual elements, establishing the framework of the suitable hybrid system from the perspective of the electromagnetic environment is crucial. This research reviews recent work on using various battery/super capacitor hybrid systems in EVs. Despite this, there is a huge amount of overlap between these two academic subjects. Many of the hybrid systems tested for EVs are constructed utilizing SCs and commercial batteries, which weren't designed for this application. The parameters for the EVs' hybrid energy systems must be the main considerations in the design of the batteries and SCs. The use of various electrode materials for batteries and SCs that might not be advantageous for ordinary uses but open up certain possibilities for EV applications is what gives the point its crucial importance. However, the battery/SC system involves more than merely combining two electrochemical power sources. Along with the individual cell layouts, the entire electrical system needs to be delicately calibrated to produce an appropriate power source [10].

The study recommends a multi-dimensional size optimization model with a hierarchical energy management technique to maximize the elements' strength and speed in a plug-in hybrid electric vehicle (PHEV) using the hybrid energy storage system (HEMS). Towards verifying the effects of size optimization as well as power management, a PHEV with a battery energy storage system (BESS) is utilized as a comparable model, as well as the dynamic programming (DP) methodology is set as a benchmark for comparisons. The system's higher power, the power and capacities of the battery, the maximum power and capacities of the super capacitor, and other factors are all examined in the size optimization approach to determine the system's ideal configuration (SC). Especially comparing to the BESS, the size-optimized HESS increases efficiency by 37.8% while lowering system capacity by 31.3%. The HEMS improves vehicle fuel efficiency while reducing battery ageing. Although the upper layer utilizes the DP technique to maximize fuel economy, the lower layer uses the linear programming (LP) technique to improve battery life. The battery ageing rate has reduced, and the vehicle efficiency was increased when compared to the benchmark, according to the size optimization and HEMS results. However, the battery employed in this study needs to be frequently charged and discharged in order to meet the power needs of the vehicle. Inevitably, this would speed up battery ageing. Power batteries are still expensive today and their cycle life hasn't improved [17].

The regulation of EVs in cooperation with ac microgrids is a crucial component of the incorporation of renewable energy sources (RES) that includes solar and wind farm–microgrids. It is well known that the variable power generation capabilities of such RESs could cause significant changes in the microgrid frequency. The results of these products are therefore viewed as continual disturbances. It used to be common practice for microgrid development to ignore the ability to allow for frequency stabilizing effects, which allowed the operator's efficiency to be ineffective in controlling the frequencies in this type of microgrids. To address this problem, a novel suggestion for EV, PV, and wind farm (WF) synchronization for MG frequency control is made in this study. The suggested adaptive PI controller is implemented in the control architecture using real-world proportional integral (PI) systems. The effects of a short delay are taken into consideration in input-output pairs of adaptable PI controllers. A virtual model has been made in order to test the proposed controller. According to simulation results, the proposed organized control method for WF, EVs, and PV electricity production offers better occurrence control performance than a fixed PI control system under a variety of unknowns, including variations in solar and wind power, the disconnection of RESs, N-1 outages, load variations, and EVs numbers. The findings indicate that the suggested adaptive synchronized controller may be applied in a PV, WF, and EV-based MG, which is appealing. The developed adaptive controllers could potentially be applied as an alternative control strategy to assist MGs in utilizing renewable energy sources. Since variable load requirements don't use frequency control, they can be seen as MG uncertainty interruptions, whether they are corporate, industrial, or residential [18].

The quick adoption of the grid-connected MG is encouraged by advantages for the economy, environment, and society. The major goal of industrial MGs is still economic viability. MGs usually include a static electrical energy storage system (ESS), which enables islanded mode and affordable regulation of primary grid use. Therefore, early research focused on the fixed ESS's size. The emergence of large-scale EV charging hub microgrids

(CHMGs), such the one situated over the freeway A8 in Augsburg, Germany, has significantly altered the economically optimum capabilities of static ESS. It is commonly known that EVs can be coupled and then compensated for static ESS, but research on how the loading strategy—instantaneous, controlled, or bidirectional—affects the financially optimal capabilities of the static ESS is still lacking in quantitative data and methodical guidelines. This paper proposes a method to narrow this gap by providing case analyses for both ESS price and EV charging strategy and using a mixed-integer linear-programming framework for planning decisions below a range of prospective ESS capabilities. The strategy thus establishes the ESS's ideal financial capacity. The results show that the static ESS sizing decision is appropriate in the CHMGs under discussion near Augsburg in all except the most extreme cases. Particularly, if > 65% of EVs begins charging immediately and the cost of storage falls to 150 EUR/kWh, the capability of the financially optimum static ESS grows. However, fewer EVs in controlled charging environments can already greatly reduce static ESS. Unexpectedly, the paper also offers quantitative evidence that bidirectional charging expenses at the CHMG in Augsburg do not necessarily have to be written off. There aren't many drawbacks to the study, and so the report might aid in streamlining and accelerating the planning process for efforts like the MG charging station. Due to the projected adoption of electric vehicles and the demand for further expansion of both the networking for charging and decentralized renewable energy resources, we foresee a significant increase in the number of such charging hubs in the future [19].

The usage of electric vehicles (EV) has expanded globally, not only as a method of realizing a low-carbon vision but also by providing ancillary services that boost the reliability of the power system. Low power factor appears to be a common problem in the present AC grids that causes a variety of problems with the quality of the electricity and has gotten worse as the use of distributed generation (DG) increases. In view of the expanding usage of EVs for extra services as well as the reduced power issue in existing electrical grids, this study thus proposed an expanded control method for three-phase MG management's power factor correction made up of dynamic loads, an EV parking lot, and a PV array. Such control method aims to handle power factor issues while permitting the complete PV production by utilizing EV charging infrastructure. To suit the needs of both MG users and EV consumers, several operational parameters are suggested using the Multi Objective Optimization (MOO) technique. In order to meet these improvement requirements, the car is charged, while the MG power factor has been altered to use a nonlinear programming technique. The results of testing the suggested control strategy in various scenarios show that the MG will continue to operate normally even in the presence of overloading and a sizable peak power surplus in the production unit. Throughout the entire analysis period, the inaccuracy is around 4.5 smaller than the networks without vehicles, and the MG power factor remains above the planned reference, resulting in a reduction in energy expenditures. The results show that a range of systems, including fixed batteries and various energy storage systems, can use the suggested control mechanism. These systems primarily consist of DG equipment and EV charging stations. A precise estimate of the variable energy cost, frequency and voltage controls, and other concerns might have been evaluated in the upcoming designs and added to the management plan as future objectives [19].

III. Problem Statement

Despite their many advantages, electric vehicles (EVs) have faced a number of difficulties, including managing battery charging, rising energy costs, a lack of charging stations, and assessment of battery life. For EVs, a variety of techniques, machine learning techniques, and artificial intelligence techniques have been suggested. The prior methods, however, have concentrated on just one or two EV components. This work suggests a hybrid deep learning strategy for managing and controlling electric vehicle charging in order to address such issues. To obtain sufficient feature data on the battery, a feature extraction process by utilizing Recursive Neural Networks (RNNs) is advised. The bidirectional gated recurrent unit framework (GRU) was subsequently constructed by the study to predict the state of the EV. The GRU receives the output of the RNNs as input, which greatly enhances the performance of the model. The RNN-much GRU's simpler structure results in lower computing performance. According to the experimental findings, the GRU technique can be used to precisely track changes in electric car mileage. A hybrid deep learning-based predictive algorithm might offer quick convergence speed as well as improved efficiency in contrast to the proper approach for creating SOC estimate over conventional models, as demonstrated by extensive real-world study.

IV. Proposed Approach for Managing and Controlling of Electric Vehicle

Initially, the data collection process is initiated. In order to build a clear dataset, the pre-processing step is included which is a crucial step in getting the input data into a form that will work better for loading. The preprocessing step involves label encoding, null value elimination, deleting duplicate data, and Eliminating Special Characters. The relevant features from the batteries are extracted using Recursive Neural Networks (RNN). Later, utilizing Gated Recurrent Units (GRU), which also precisely records electric vehicle miles, the status of the electric vehicle is predicted by accessing the battery features. Lastly, the performance of the suggested solution is assessed using certain metrics and compared to existing approaches. Fig. 2 shows the RNN-GRU workflow for managing Electric Vehicle.

A. Dataset

A method for managing and controlling the electric vehicle was established by the study. As a result, the data set includes electric vehicle effectiveness and battery features that were gathered from the Kaggle platform. Data scientists and machine learning enthusiasts can connect online at Kaggle. The mtcars dataset is one of the more well-known data science datasets. ElectricCarDataClean.csv file, from mtcars Kaggle dataset, is used in this study.

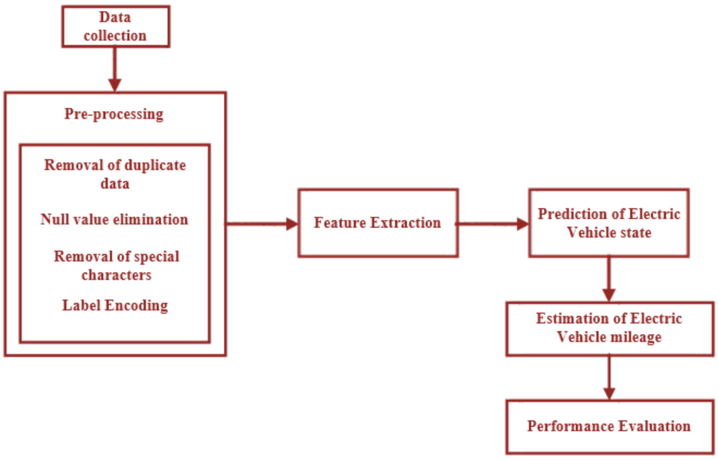

Fig. 2. RNN-GRU workflow for managing EV.

TABLE I: DATASET OF ELECTRIC VEHICLES

Brand	AccelSec	Top Speed	Range	Efficiency	FastCharge	RapidCharge	PowerTrain	PlugType
Tesla	4.6	233	450	161	940	Yes	AWD	Type 2 CCS
Volkswagen	10.0	160	270	167	250	Yes	RWD	Type 2 CCS
Polestar	4.7	210	400	181	620	Yes	AWD	Type 2 CCS
BMW	6.8	180	360	206	560	Yes	RWD	Type 2 CCS
Honda	9.5	145	170	168	190	yes	RWD	Type 2 CCS

Several features are included in the dataset collection, including the car's brand, rapid charging, acceleration, power train, plug type, etc. Nevertheless, the pre-processing stage is entangled in the data cleaning process and the dataset needs to be cleaned with user experience. Table I shows the dataset utilised for this proposed RNN-GRU approach.

B. Preprocessing

Preprocessing is a crucial step in getting the input data into a form that will work better for loading into the created model. The raw information gathered from the environment is unsuitable for further processing. Due to the chance that they may have missing data, duplicate data, and irrelevant feature data. As a result, it is preprocessed to create a clear dataset, which includes label encoding, null value elimination of the cases by removing duplicate data and Eliminating Special Characters. When two or more rows contain numbers that are similar or identical, there are duplicate observations. Duplicate data are eliminated by identifying the shared feature values between many instances. Label encoding involves converting labels into a quantitative form so that machines can read them. For the organized dataset, it is a key supervised learning pre-processing stage. Special Characters are removed during the assignment of polarity must be eliminated by removing special characters like [] and ()/'. Sometimes, if the special letters aren't eliminated, they could combine with the words and prevent certain words from appearing in dictionaries.

C. Feature Extraction with RNN

The electrochemical chemistry taking place inside an electric vehicle battery is sophisticated and displays extensive nonlinear behaviour. The long-term error accumulation will cause a significant decline in the SOC's prediction accuracy. Deep Learning (DL) makes use of a hierarchical idea system to comprehend complicated actual behaviour by gaining knowledge from information. Additionally, the long-term error accumulation impact brought on through prediction model, which can be avoided by understanding the nonlinear behaviour of the battery. As a result, it is appropriate for studying the battery's nonlinear behaviour. The chapter then goes over the fundamentals of RNN and establishes the theoretical framework. Assuming there is a parse tree $T_2(T_1 + ab)c)$as depicted in Fig.3 And the three words a, b, c are shown on, correspondingly, as their internal representation of $a, b, c \in o^n$.

In a bottom-up fashion, parent node representations are calculated. Additionally, to calculate the parent node, the study utilized a neural network that has weight matrices $D_1 \in o^{n*n}$ for left children and $D_2 \in o^{n*n}$ for right children. It is assumed that there is a vector representation T_1 for each parent node$T$. As a result, $T_1$is calculated using (1).

$$T_1 = f(D_1 a + D_2 b + y) \quad (1)$$

where, f is activation function while y is a bias vector.

Up until the root node, the procedure continues. An adaptive RNN method is employed for feature extraction, which retrieve the battery status information to solve this issue.

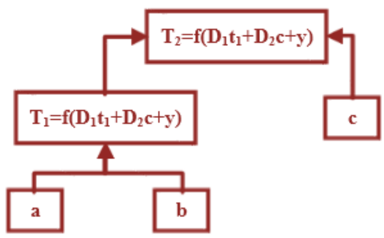

Fig. 3. Parse tree structure of Recursive Neural Network.

Since the network structure's structural as well as hierarchical characteristics, RNN can be used with any hierarchical structure. The input battery state data might well be substantially deconstructed to extract architectural feature data when the battery feature information is retrieved, completing the improved representation of the battery state data. RNN has strong logical reasoning capabilities and could fully utilize their capabilities in extracting the features as compared to statistics-based feature extracting algorithms. The RNNs-based model creates the state variables to represent the battery state information by extracting the battery feature.

V. Prediction of Electric Vehicle State using GRU

A type of Recurrent Neural Network is the GRU. It has also been suggested to concentrate on the issues of long-term memory as well as a gradient in back-propagation, similar to LSTM (long short-term memory) [18]. In this work, GRU is utilized since it performs similarly to LSTM but costs less to compute. The framework of the GRU is depicted in Fig. 4. The update gate c_h, the reset gate s_h, the hidden state t_{h-1}, the current inputa_h, and the hidden state t_h make up the GRU. The input to GRU in the subsequent procedure is $a_h$and t_{h-1}, and the output is t_h.

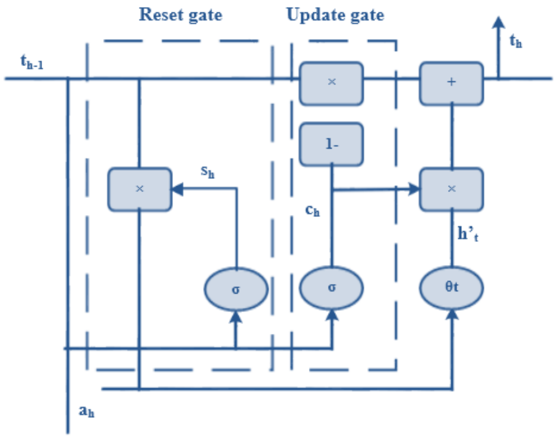

Fig. 4. Framework of Gated Recurrent Unit.

A. Update Gate

The degree of the knowledge from the previous instant is integrated within the present state is managed by the update gate c_h. More data is received from the preceding moment if the update gate's value is higher. Calculating the update gate c_h is given in (2).

$$c_h = \sigma(D_c, [c_{h-1}, a_h] + y_c) \quad (2)$$

Here D_c and y_c stand for the update gate's weight matrices and bias, respectively. The equation $\sigma(a) = 1/[1 + \exp(-a)]$ denotes the sigmoidal function that transforms the input into values between 0 and 1 which is substituted as the gate control signal.

B. Reset Gate

The amount of information from the preceding hidden layer that needs to be removed is managed by the reset gate s_h. It can be determined using (3).

$$s_h = \sigma(D_s, [c_{h-1}, a_h] + y_s \quad (3)$$

Here D_s and y_s stand for the reset gate's weight matrix and bias, correspondingly. The outcome of the reset gate would be set as 0 by sigmoid to erase the memory of the hidden state of the preceding moment if it is not necessary to recall it. The output of the reset gate would be set to 1, on the other hand, by sigmoid, allowing all hidden states from the preceding moment to complete. In other words, the lesser the reset gate, the less data is taken from the prior state.

C. Output State

A calculation for the output state $\bar{t}_h$ is in (4).

$$t'_h = \theta t(D_t. [s_h * t_{h-1}, a_h] + y_t) \quad (4)$$

Here D_t and y_t are, correspondingly, the weight matrix as well as bias of the potential output state t'_h. θt turns on the Hadamard Product function $*$, which multiplies the matching matrix members, towards scaling the data to a series from -1 to 1. The output state of the GRU is directly impacted by the reset gate's output. The amount of neuron's output is stored from the preceding moment depends on the value of a_h with the hidden layer state at the time in question. The output of the neuron is kept from the preceding moment to a higher extent the higher the value of a_h.

D. Hidden State

The hidden layer state t_h, which is produced by GRU, established by c_h, t_{h-1} and t'_h. Equation (5) gives the mathematical expression:

$$t_h = (1 - c_h) * t_{h-1} + c_h * t'_h. \quad (5)$$

The higher the dependency of t_h on t'_h the less the influence of t_{h-1} on the output, and the larger the c_h. (1-c_h) t_{h-1} denotes the selective "forgetting" of the prior hidden state, while t_{h-1}, $c_h * t'_h$. denotes the selective "memory" of the current node information. GRU incorporates the data from the input series of both the backward and forward directions, in contrast to typical GRU that may predict the outcome of the instant depending upon the temporal series data of the preceding moment. It could have two hidden layers containing GRU units that communicate information in the opposing ways.

The input a_h provides the hidden layers in multiple opposing ways at the same time at time h. Such one-way hidden layers work together to determine the output y_h at time h. The forward GRU contains information about moment h with the input sequence's earlier moment, whereas the backward GRU contains information about moment h with the input sequence's later moment. The GRU's hidden layer propagation system is described as Equation (6)-(8).

$$\overrightarrow{t_h} = f(\vec{D}a_h + \vec{P}\,\overrightarrow{t_{h-1}} + \vec{y}) \quad (6)$$

$$\overleftarrow{t_h} = f(\overleftarrow{D}a_h + \overleftarrow{P}\,\overleftarrow{t_{h-1}} + \overleftarrow{y}) \quad (7)$$

$$b_h = \alpha(\overrightarrow{t_h}, \overleftarrow{t_h}) \quad (8)$$

Here $\vec{D}$, $\vec{P}$, $\overleftarrow{D}$, $\overleftarrow{P}$ stand for the weight of hidden layer with the input layer, which is the preceding moment in forward and backward computation, respectively; $\overrightarrow{t_h}$ and $\overleftarrow{t_h}$respectively denote the hidden-layer state of forward and backward computation; and $\vec{y}$ and $\overleftarrow{y}$ respectively denote the bias of forward and backward calculation. The hidden state could substantially enhance the model's ability to interpret nonlinear data by capturing the forward and backward dependency within time of the battery as well as predicting the condition of the electric vehicle. Consequently, it makes sense to assess the state of the vehicle using a GRU structure.

VI. Estimation of the Electric Vehicle Mileage

As a measurement point, the accumulated mileage is calculated using the GRU network; the estimation value is enhanced by using GRU. In this study, the state functions as well as measurement function of range estimation are written as (9) and (10).

$$R_{f,h} = R_{f,h-1} + \frac{EV_{h-1}+EV_h}{2}\Delta S + n_{h-1} \tag{9}$$

$$b_h = R_{m,h} + EV_h \tag{10}$$

The movement of the electric vehicle from time $h-1$ to time h is assumed by the state function to be a unified acceleration motion, however the actual situation could differ, thus the state estimation also considers the structure oscillation noise n_{h-1}. The prediction outcomes of the GRU system in the measurement function do experience some oscillations and errors.

To combine the two components of the results and get the best range estimation for electric vehicles, the measurement noise EV_h, portion of the error is used. The RNN-GRU technique's framework is depicted in Fig. 5, where "ΔS" denotes the sample period, EV_{h-1}, EV_h and "ob k," respectively, indicate the speed of an electric vehicle as measured by the sensor at time steps h and $h-1$. S represents the output of the GRU network at time h, $R_{f,h}$, and ΔS indicates the output range of the average speed technique at time h.

In this approach, the mileage determined using the average speed method is referred to as the observational value and the outcome of the GRU networking by the "measured value" of the distance.

A. Performance Metrics

The predictive performance of the suggested approach is evaluated in this research utilizing the regression assessments, Mean Square Error (MSE) and Mean Absolute Error (MAE). The projected value is nearer to the true value and the prediction method performs better when MAE and MSE are less. Equation (11) and (12) defines MSE and MAE.

$$mean\ error\ square = \frac{1}{M}\sum_{i=1}^{M}(b_i - \widehat{b_i})^2 \tag{11}$$

$$mean\ absolute\ error = \frac{1}{M}\sum_{i=1}^{M}|b_i - \widehat{b_i}| \tag{12}$$

Here, $b_i, \widehat{b_i}$ respectively indicates the actual value and the prediction value, and M indicates the amount of sampling points.

VII. Results and Discussion

The proposed RNN-GRU approach's effectiveness is demonstrated through tests and simulation. Resolving the context dependent transition probabilities in the feature extraction framework is a challenging that will determine if all the battery's features could be extracted.

The vehicle's condition is estimated using the GRU-based prediction model that can also precisely track the electric vehicle's mileage. The configuration of RNN-GRU is given in Table II.

TABLE II: Configuration of RNN-GRU

Layer (type)	Output Shape	Param #
embedding_10 (Embedding)	(None, None, 64)	64000
gru_10 (GRU)	(None, None, 256)	247296
simple_rnn_10 (SimpleRNN)	(None, 128)	49280
dense_10 (Dense)	(None, 10)	1290

Without losing generality, the study compared the RNN-GRU technique described in this research to other methods as well as demonstrates the estimation results of the model using data from electric vehicles.

A hidden layer-containing RNN-GRU network is trained using the Adam optimizer. It is clear that the model converges quickly, demonstrating the RNN-GRU network's ability to immediately pick up on the mapping link between input variables and mileage.

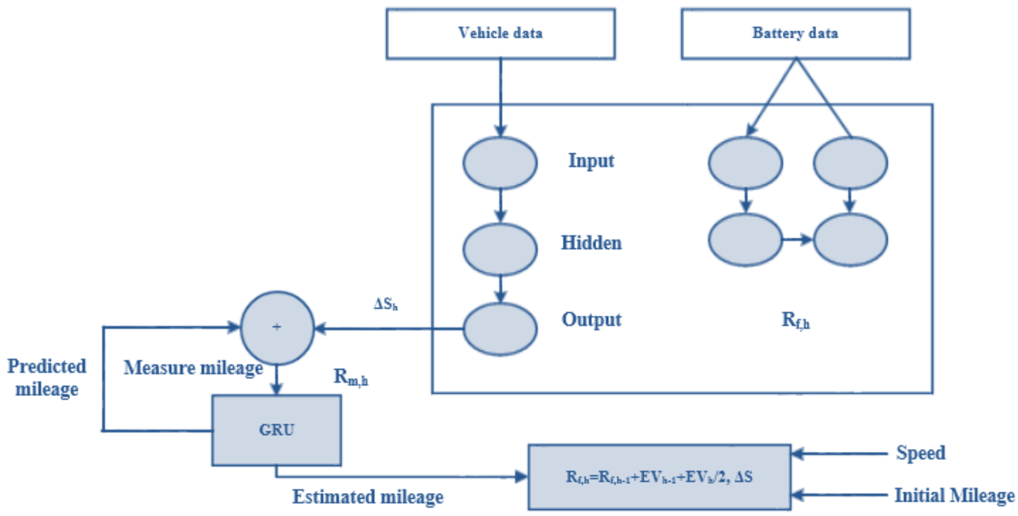

Fig. 5. Structure of RNN-GRU approach.

TABLE III: COMPARISON OUTCOME OF VARIOUS METHODS

Methods	MSE	MAE
GRU	1.29	0.91
LSTM	0.80	0.72
ANN	9.80	2.30
MLR	4.01	1.77
RNN-GRU	0.92	0.70

Table III displays a comparative of MAE and MSE. The MAE and MSE of the time series network structure are fewer than those of the conventional multivariate regression model, the tree-based model, and also lower than those of the ANN model, as can be observed in Table III. It aims to ensure that the operating data of the electric vehicle prior to the anticipated time can also be taken into account by data set network architectures like RNN-GRU and LSTM.

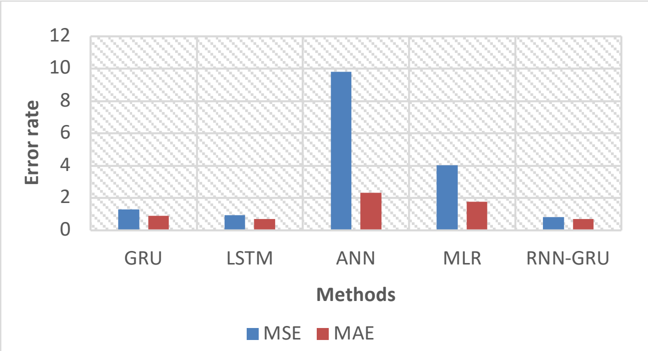

Fig. 6. Comparison of estimation error.

Six models, including GRU, RNN-GRU, LSTM, ANN, and MLR, was compared for estimating the mileage of electric vehicles to calculate and validate the efficiency of the suggested strategy. In Fig. 6, the estimation error is displayed. The estimation error of the RNN-GRU approach is shown to vary about zero value, demonstrating that it estimates the mileage of electric vehicles more accurately than other methods than the ANN method, which has a significant estimation error.

The network model has less error rate because the mileage represents the total outcome of each period. To establish a better balance between performance and speed as well as to make it easier for the model to be used in real-world circumstances, the RNN-GRU technique was chosen for this work.

VIII. CONCLUSION

Electric Vehicles (EVs) are a threat to conventional gasoline vehicles in regard to their environmental acceptability as well as energy efficiency. The prediction of states related to EV charging could help in determining the upcoming charging requirements of EV consumers. In particular, it could control how charging infrastructure is operated and managed and give personalized charger capacity statistics depending on users' current locations. The accurate method of EV charging state estimations is thus an emerging problem.

In this study, a hybrid deep learning technique is recommended to guarantee safe and reliable charging operations that guard against overcharging or undercharging the battery.

To acquire adequate feature data on the battery, an extracting features model is developed based on Recursive Neural Networks (RNNs) is advised. To predict the state of the EV, the study then created the gated recurrent unit framework (GRU). The GRU receives the result of the RNNs as input, and greatly enhances the effectiveness of the model. The RNN-much GRU's simpler structure results in lower computing performance.

The testing outcomes demonstrate that the GRU technique can accurately track the mileage of an electric vehicle. A hybrid deep learning-based predictive algorithm could offer quick convergence speed and less error rate in comparison to the right approach for mileage estimation over traditional models, as demonstrated by the thorough real-world experiments.

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