Available Capacity Computation Model Based on Long Short-Term Memory Recurrent Neural Network for Gelled-Electrolyte Batteries in Golf Carts

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This work was supported by the Ministry of Science and Technology of Taiwan under Grants MOST-111-2622-8-005-003-TE1, Grant MOST-110-2622-8-005-005-TE1, Grant MOST-110-3116-F-008-002, and Grant MOST 110-2622-E-005-002-CC2.

ABSTRACT A deep neural network model for the investigation of the discharging voltage, temperature, cycle, and state of charge-dependent behavior of gel batteries is presented in this paper. The proposed model utilizes a long short-term memory recurrent neural network to investigate the estimation of the state of charge and the state of health. The model could serve as a management strategy for the Vehicle Service Management Centers to reduce maintenance costs by regulating the battery status, managing the driving paths, adjusting the driving areas, and replacing the batteries in batches. The management strategy utilizes the state of charge and the state of health of gel batteries as key variables in assigning driving paths and areas to golf carts. In the actual on-road experiment, the model successfully tested and verified the state of charge of the gel batteries in the golf cart with a mean absolute error of 0.376% which was better than the feedforward neural network of 2.8% and the recurrent neural network of 1.7%. These results indicate that the model can accurately estimate the state of charge and the remaining service life of batteries which provide clear indicators for the vehicle service management systems.

INDEX TERMS Vehicle service management system, gelled-electrolyte battery, state of charge (SoC), state of health (SoH), long short-term memory recurrent neural network (LSTM), golf cart.

NOMENCLATURE

Acronyms:

| Acronym | Description                      |
|---------|----------------------------------|
| AGM     | Absorbed Glass Mat.             |
| ANN     | Artificial Neural Network.      |
| BMS     | Battery Management System.      |
| CC - CV | Constant-Current and Constant-Voltage. |
| DoD     | Depth of Discharge.             |
| EVs     | Electric Vehicles.              |
| FNN     | Feedforward Neural Network.     |
| LEVs    | Light Electric Vehicles.        |
| LSTM    | Long Short-Term Memory.         |
| MAE     | Mean absolute error.            |
| mSoH    | Measured SoH of the battery system. |
| pSoH    | Predicted SoH of the battery system. |
| RNN     | Recurrent neural network.        |
| SoC     | State of Charge.                |
| SoH     | State of Health.                |
| VRLA    | Valve-Regulated Lead-Acid.      |
| VSMC    | Vehicle Service Management Centers. |

Variables:

| Symbol | Description                                      |
|--------|--------------------------------------------------|
| C_{max,p} | The battery’s maximum usable capacity.           |
| C_n    | The rated capacity.                             |
| Cost   | Maintenance process.                            |
| d_t    | The discharging time.                           |
| f_{bat} | Purchase expense of a set of gel batteries.     |
| f_{lab} | The labor cost to change the batteries.         |
| f_{ta} | The transportation allowance charged by the manufacturer. |
| I      | The battery current.                            |
| i      | The discharging current.                        |

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Liu.
**I. INTRODUCTION**

The issues on energy conservation and environmental protection have been receiving attention which contributed to the advancements in electric vehicles (EVs) or light electric vehicles (LEV) [1]–[3]. The lead-acid battery is widely used in the majority of LEVs, such as golf carts and electric scooters due to low costs, ruggedness, high reliability, and the ability to supply instantaneous large current [4], [5].

However, the traditional lead-acid battery has a short cycle life accompanied by electrolyte leakage, sedimentation of particles at the electrode, and gassing which may cause the shedding of active material [6]. The valve-regulated lead-acid (VRLA) battery can improve the disadvantages of lead-acid batteries through immobilized electrolytes to achieve internal oxygen cycles as seen in the use of a glass mat separator that wicks the electrolyte solution (absorbed glass mat or AGM battery) or the use of SiO2 as a gel to turn the acid inside the battery into thick liquid (gel battery) [7]–[9].

Immobilizing liquid electrolytes can improve the performance of lead-acid batteries significantly. When comparing gel batteries with the AGM batteries, the use of fumed silica can overcome the stratification of electrodes in the gel battery [10]. The three-dimensional network structure of the gelling agent prevents precipitation in the lead-acid battery during electrochemical reactions. Having the electrolyte in gel form provides several advantages than in liquid form which includes being maintenance free with no need to refill water, does not require special ventilation for the acid fumes, has minimal to none acid electrolyte leakage, has less corrosion to prevent the battery from drying out, and the battery can be installed in any desired orientation [11], [12]. Golf carts are driven on roads or grass and due to inexpensiveness, the safety control system for batteries is a simple battery management system (BMS) in addition to the heat sink cooling component. The operating temperature of the battery strongly affects the SoC and remaining service life estimation.

**A. THE PROBLEMS WITH USING BATTERIES AS A POWER SOURCE IN GOLF CARTS**

Golf carts use batteries as motive power and the operating environment is more demanding than fueled vehicles with ignition systems because of the frequent charging and discharging. Additional heat is generated inside the battery from chemical reactions. AGM battery has a relatively small amount of electrolyte. When the temperature of the operating environment is too high or if the charger fails, the charge rate will increase rapidly and cause the temperature of the battery to rise beyond normal. The AGM battery can expand and deform with significant water loss. This is called thermal runaway which can result in battery failure and greatly affect the operation of LEVs. A gel battery is better suited for power storage in LEVs because gel batteries comprise of a quasi-flooded electrolyte design which results in a larger heat capacity, greatly reduces the possibility of thermal runaway, extends the cycle life, improves the low-temperature discharge capacity, and widens the range of operating temperatures [10], [13].

In order to study battery safety, researchers have tried to define the operating area for batteries based on the discharge characteristics, but have not identified the means to numerically quantify the area. Aside from the load voltage and discharge current of a battery, the status of a battery, such as SoC, SoH, etc., cannot be accurately estimated.

SoC represents the available capacity of batteries and is often expressed as a percentage of the battery’s rated capacity. SoC estimations based on the ampere-hour method are evaluated as a function of time and current. SoC and SoH are closely related, as shown in [14], and use maximum usable capacity instead of rated capacity as the maximum amount of charge to correct the aging error of batteries as shown in

\[
\text{SoC}(t) = \text{SoC}(0) - \frac{1}{C_{\text{max},p}(t)} \int_{t_0}^{t} I(t) dt
\]

\[
\text{SoC} = \frac{Q_{\text{available}}}{C_{\text{max},p}}
\]

where \(C_{\text{max},p}\) is the battery’s maximum usable capacity and \(I\) is the battery current at time \(t\). \(Q_{\text{available}}\) is the battery’s available capacity for the charging/discharging cycle.

SoH refers to the ratio of the battery’s remaining capacity to the new battery’s rated capacity. It is an important indicator for battery replacement. SoH can be expressed as

\[
\text{SoH} = \frac{C_{\text{max},p}}{C_n} \cdot 100\%
\]

where \(C_n\) is rated capacity.

An overview of the methods for the estimation of a variety of battery states has already been described. The common methods, among the electrical circuit model, are the Coulomb counting, open-circuit voltage (OCV), and extended Kalman filter [15]–[18]. The analytical model is a macroscopic model which employs the performance-relevant characterization of given systems [19]–[21]. The electrochemical model can predict the limitations of physical cells which affects automotive applications [15]–[17]. The stochastic model, particularly the Markov chain processes, can model battery-powered systems as a whole [22], [23]. A typical model should be able to simulate the actual charging or discharging behaviors in various temperatures then analyze the remaining capacity of a battery. In general, the electrochemical models are solved numerically [24]–[26] by utilizing partial differential equations to model the electrochemistry reactions of the electrolyte and both electrodes [27]. Since electrochemical models can provide physics insight into the chemical components of a battery, they are preferred in the SoH estimation and in
tracking battery degradation. However, the electrochemical model is difficult to set up along with complicated parameters which may require high-level computational devices and is time consuming. Thus, the computation is less desirable, particularly in the implementation of computationally battery management systems for EVs.

**B. THE MACHINE-LEARNING MODEL FOR SoC AND SoH IN BATTERY ESTIMATIONS**

The battery’s state of estimation from data-driven machine learning has been supported by advancements in communication networks and cloud computing. Large amounts of data on the status of the battery have been collected and analyzed in a partial or complete automated manner to improve the accuracy of the status from which the reliability and safety can be further improved [28].

The data-driven machine learning obtains the battery’s capacity fade during the charging and discharging processes. It does not explain the internal material’s aging process unlike the electrochemistry laws or circuit models. Specifically, the data-driven method is strongly dependent on the number of previous experiences. In work [29], support vector machines were used to predict the SoC and SoH of lithium-ion batteries.

To improve the accuracy of SoC predictions, an online multi-level support vector machine method has been designed [28], [30] which uses the battery’s voltage, current, and temperature as characteristic parameters to improve the accuracy of the SoC. However, these methods require a vast amount of data to develop the pattern of the battery’s capacity fade otherwise prediction accuracy cannot be guaranteed.

Recently, Feedforward Neural Network (FNN) and Recurrent neural network (RNN) used the estimation of the dynamic state of batteries to predict the SoC [31]. As the number of cycles increased, RNN long-term dependence issues were presented [32]. Long short-term memory (LSTM) can be used to reflect the long-term memory of battery aging trends. In addition, in work [33]–[37] proposed a combination of LSTM with other models to obtain the SoC and SoH predictions. Even though researchers depend on the training and testing data sets from a laboratory, there is still no guarantee that the SoC and SoH can be estimated accurately on actual EVs.

In order to verify that the LSTM can significantly improve the prediction accuracy in actual cases, battery training sets were used in the laboratory; the BMS in the electric golf cart collected testing data sets on the gel battery’s voltage, current, temperature, and discharging time while the vehicle was in motion. Compared with FNN and RNN, the experimental results of the proposed model have a shorter computing time, higher efficiency, and accuracy. It could also use the number of cycles to evaluate SoC and the remaining battery capacity under various cycles. Coulomb count measurements were compared to results under various cycles to verify the proposed model.

In order to assist vehicle management centers in regards to electric golf carts, the LSTM accurately calculates the SoC and SoH of gel batteries. The appropriate driving paths and areas are planned where the aging level of batteries is kept as consistent as possible. This strategy also allows batteries to be replaced in batches to save costs.

In summary, the main goal of this paper is to present the application of the LSTM in estimating the SoC and SoH. This paper compares FNN and RNN, then LSTM is used to compute driving paths for golf carts in order to confirm the validity and accuracy of the model, and is used in our golf cart operation center to assign driving paths to transport passengers and merchandise on campus. In addition, extended research results take into account that the batteries should be replaced when considering the management and maintenance of the electric golf carts in the operation center, and when maximizing the benefits and minimizing the maintenance costs. Many studies have presented LSTM in the context of battery estimation, but our research is more practical and extensive.

**II. EXPERIMENTAL SETUP AND PROCEDURES**

Figure 1 illustrates the discharging curve of gel batteries. During discharge, the voltage drops from 12.8V to 11.5V and the SoC is around 25%. The curve is smooth and close to linear which means that the working area is stable and has high efficiency. When the voltage drops from 11.5V to 10.5V, the SoC is at 10% and the curve is non-linear which indicates that the battery is about to run out.

![FIGURE 1. The characteristic of a discharge capacity curve for gel batteries consisting of a smooth and linear curve, a voltage turning point, and a non-linear curve.](image-url)

In almost all known rechargeable battery types, such as lead-acid batteries and lithium batteries, there is a correlation between the depth of discharge (DoD) and the lifetime of the battery. DoD is defined as the total amount of energy discharged from a battery divided by the rated capacity. Hence, the battery is rarely fully discharged to maintain its lifetime [38]–[41]. In order to extend the lifetime, the cut-off voltage is set to 11.5V for the training batteries in the electronic load and the testing batteries in the golf cart.
TABLE 1. The specifications for the operating environment of training batteries.

| Battery serial number | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 |
|-----------------------|----|----|----|----|----|----|----|----|----|----|----|----|
| Discharging current (A)| 3.9| 7.8|    |    |    |    |    |    |    |    |    |    |
| Operating temperature (°C) | 10 | 20 | 35 | 50 | 10 | 20 | 35 | 50 | 10 | 20 | 35 | 50 |

A. EXPERIMENTAL SETUP

The Chroma 17020 battery module test system was used to measure the discharge characteristics of gel batteries in this study. The rated capacity of the gel batteries used in this experiment was 26 AH. The training time for each battery was three months with a total of twelve training batteries at 60 USD per battery. The batteries were charged by the constant-current and constant-voltage (CC-CV) method until the voltage reached 14 V, then were left idle for a certain period to ensure that the batteries reached a steady state. According to Table 1, each battery was discharged at a constant discharging current until the voltage dropped to the cut-off voltage of 11.5 V. The process flow diagram for the experiment is illustrated in Figure 2. All tested batteries were cyclically charged and discharged 300 times. The curves of the discharging behavior for brand new, 50-, 100-, 150-, 200-, 250- and 300-cycle batteries under different temperatures are illustrated in Figure 3(a-d), respectively. The data acquired from the experiment were used as the training set for the LSTM. Hence, the relationship between the variation in capacity, temperature, and the number of cycles can be investigated.

B. DISCHARGE CURVES ANALYSIS OF BATTERIES UNDER DIFFERENT TEMPERATURES AND NUMBER OF CYCLES

The batteries were cycled 300 times under different temperatures. Characteristics of the discharging behaviors and voltage variation with time of the gel batteries exhibited a curve with linear plateau voltage. In Figure 3, when a new battery is discharged at higher temperatures, the rate of the discharge reactions is increased as temperature increases, but so does the rate of life-limiting side reactions (may be corrosion). Hence, elevated temperatures can reduce longevity as seen from the 300 cycles curve in Figure 3(d).

Except for the illustration shown Figure 3(c), the common characteristic of the batteries is that after 250 cycles, the SoC decreases rapidly. The results indicate that the optimum operating temperature of the gel battery is approximately 35°C. In this temperature range, the cycle life of the gel battery is extended.

III. MODEL DEVELOPMENT

A. BASIC CONCEPT OF FEEDFORWARD NEURAL NETWORKS AND RECURRENT NEURAL NETWORKS

FNN is one of the simplest neural networks which implements non-linear mappings with an arbitrary number of inputs and outputs [1]. Figure 4 mainly introduces the basic model of artificial neural network (ANN) and its advances. Figure 4(a) shows the basic FNN-based structure, taking as an example of battery states estimation, which includes: (1) an inputs layer: the input variables, such as discharge voltage and current and temperature; (2) one or more hidden layers; (3) an output layer: the output results, such as SoC or SoH; Apart from this, the non-linear activation function f must also be considered. Generally, the hyperbolic tangent function (sigmoid) or the rectified linear unit (RELU) is used. The former limits the output to values between 1 and −1, the latter chooses and consists of a function that sets all the negative input values to zero.

In this paper, the performance of LSTM is compared to FNN and RNN. FNN consists of three layers: the input layer, the hidden layer, and the output layer. According to Kolmogorov’s rule [42], [43], the numbers of neurons in each layer are as follows: (1) The input layer has four neurons with a sigmoid transfer function. (2) The hidden layer has fifteen neurons with a sigmoid transfer function. (3) The output layer has one neuron with a linear transfer function.

In other words, the concept of FNN can be represented by a function, as shown in

\[ \text{SoC} = f(i, t_c, v, d_t) \]  (4)

where \( i \) is the discharging current, \( t_c \) is the ambient temperature, \( v \) is the discharging voltage, and \( d_t \) is the discharging time.
The RNN is a sequential network instead of a feedforward network which is a combinational network, as shown in Figure 4(b). Most of the traditional neural networks are combinational networks whose computing steps from the input layer to hidden layers and output layer are executed without recurrent back to the previous or following layers. That is, each layer has its independent computing without referring to the neighbor layers.

RNNs are causal systems whose predicted results highly depend on the previous results. The computing node of the hidden layer will receive its previous output as the next input to form a recurrence loop of computing. Therefore, some memory units must exist to restore the current output for the next input.

The difference between the RNN and FNN is that RNN uses previous output data as the input data for the new time step. It means that when calculating the output of the new time step, previous calculation data needs to be included.

The new time step and the output at the time step can be expressed using (5) and (6), respectively.

\[
    h_t = f_w(W_{hh} \cdot h_{(t-1)} + W_{xh} \cdot x_t) \tag{5}
\]

\[
    u_t = W_{hy} \cdot h_t \tag{6}
\]

where \( h_t \) is the current state value, \( h_{(t-1)} \) is the previous time step, \( W_{hh} \) and \( W_{xh} \) indicate weights, and \( f_w \) is an activation sigmoid function.

\( h_{(t-1)} \) at the previous time step is multiplied by \( W_{hh} \), then added to the current input data which is multiplied by \( W_{xh} \). Subsequently, it is multiplied by the activation function to calculate \( h_t \). The results of computation depend on \( f_w \) being used. Finally, regression analysis is performed on the output by multiplying the previously calculated value by the weight.

**B. LONG SHORT-TERM MEMORY (LSTM) MODEL**

LSTM model is a variation of RNN which uses past information in a closed-loop manner. A neural network can be made.
Typical architectures of (a) FNN, (b) RNN, and (c) LSTM with their respective input data formats. $V_i$, $I_i$, $SoC_i$, and $T_i$ are battery voltage, current, state of charge, and temperature profiles, respectively, for time sample point $i$. Recurrent simply by passing the network output, an intermediate state, as an input.

The main purpose of LSTM is to improve the problems of long-term dependencies in the problem of the hidden layer of RNN. LSTM block contains a memory cell with three non-linear extra gates including the forget gate, input gate, and output gate. From the view of dataflow, each LSTM block has four inputs and one output.

The memory cell is the past time data bridge to the currently available data [36], [37]. The capacity to recall past information makes this method especially useful in solving problems that require long sequential data or time series, such as the SoC and SoH of the battery [38]. LSTM operating principles refer to works [42]–[45], as shown in Figure 4(c) and are described below.

$X$ is the input data to the LSTM block at some time instant. $f(x)$ is a sigmoid activation function, and $g(x)$ and $h(x)$ are hyperbolic activation functions. $R$, $P$, $W$, and $Q$ are weights, $b$ is bias, and $t$ is the time step.

The input gate is designed to decide whether the new message should be stored into the cell state. When the input gate is open, $i_t = f(P_tX_t + b_t)$, $C_{update} = g(W_tX_t + b_t)$.
and \( C_{t-1} = i_t \cdot C_{\text{update}} \). When \( i_t = 1 \), the memory cell is updated to 0, otherwise, it is not updated.

The forget gate is designed to determine whether it needs to be discarded from the cell state and is defined as 
\[
\tilde{f}_t = f(Q_f X_t + b_f).
\]
When \( \tilde{f}_t \) is 1, then \( C_{t-1} \) is preserved, otherwise, it is cancelled.

The memory cell can be updated as 
\[
C_t = \tilde{f}_t \cdot C_{t-1} + i_t \cdot C_{\text{update}}.
\]
Then, \( h_t = \tanh(C_t) \).

The output gate is designed to decide which message will be converted from the cell state into the current hidden layer data and is defined as 
\[
O_t = f(R_o X_t + b_o).
\]
When \( O_t \) is 1, the output gate is readable and when \( O_t = 0 \), it is not readable.

Finally, \( O_t \) is multiplied by the output of the sigmoid function: 
\[
h_t = O_t \cdot \tanh(C_t).
\]

IV. RESULTS AND DISCUSSION

In this study, all analyses were carried out using Matlab with the deep learning toolbox. As the focus of this paper is to present the benefits of using the LSTM model to improve the estimation process of the SoC and SoH, the LSTM model and a set of hyperparameters were selected then compared with other methods, such as FNN and RNN.

In preparing the testing set for LSTM, the tested LEV is a golf cart with four gel batteries as shown in Figure 5. The batteries were connected in series and sealed into a battery pack. In order to improve measurements, the battery pack was regarded as a 48 V battery. The golf cart had a BMS which can record voltage, current, time, and temperature while using a fan to keep the battery temperature consistent. The studied vehicle performed 200 drivings (discharging) and 200 charging during the tested days. For each testing day, the average temperature was recorded. Batteries were fully discharged and charged to the default cut-off voltage (46 V to 51.2 V) as much as possible.

A. LSTM MODEL SETUP

Before the LSTM training process, the battery test data was divided into training and test datasets. The training datasets consisted of all the discharging characteristics for each battery. The test datasets were the four gel batteries in the golf cart. While the golf cart is on the road, the battery’s voltage, SoC, and environmental temperature changes were all recorded by an electronic recorder. The datasets collected information on the batteries during 200 drivings. The battery data that were acquired and used as an input were the battery terminal voltage \( V \), current \( I \), discharging time \( D_t \), and operating environment temperature \( T \). The battery ampere-hours were calculated by a computer during the data acquisition and were used as a reference to calculating the SoC estimation cost during training.

B. SELECTION OF HYPERPARAMETERS

The hyperparameters are instead the properties that control the entire training process. They included variables that determine the network structure and variables which determine how the network is trained. The model’s inbuilt configuration variables include: learning rate, learning rate drop factor, learning rate drop period, number of epochs for training, minibatch size, hidden layers, hidden units, activations functions, and optimizer type, etc. The hyperparameters directly control the behavior of the training algorithm which has an important impact on the performance of the model under training. Generally, the hyperparameters of the LSTM network need to be empirically optimized to obtain higher model accuracy. This work aims to represent the benefits of the LSTM in predicting the battery’s SoC in real EVs. Hence, the hyperparameters refer [42]–[45] are configured as shown in Table 2.

| Table 2. Training hyperparameters for the LSTM model. |
|------------------------------------------------------|
| Name                              | Setting          |
|-----------------------------------|------------------|
| Number of neurons in the input layer | 4                |
| Number of neurons in the output layer | 1                |
| Number of neurons in the hidden layer | 20               |
| Loss function                     | MAE              |
| Loss function optimizer           | ADAM             |
| Activation function               | RELU             |
| Number of epochs                  | 3000             |
| Steps per epoch                   | 50               |
| Minibatches                      | 60               |
| Dropout                           | 0.02             |
| Recurrent                         | dropout 0.3      |

Figure 6 shows the performance relationship between the MAEs (Mean absolute error) and the epoch numbers.
TABLE 3. Reported SoC estimations for different battery types.

| Author                  | Measurement Model | Lowest Error | Battery Type                  | Multi-Temperature consideration |
|-------------------------|-------------------|--------------|-------------------------------|----------------------------------|
| Ephrem Chemali [46]     | SoC               | 0.573%(MAE)  | LiNiCoAlO₂                     | 0°, 10°, 25°                     |
| Xiangbao Song [47]      | SoC               | 0.1%(MAE)    | LiFePO₄                        | 0°, 10°, 20°, 30°, 40°C, 50°      |
| Zhuo Wang [48]          | SoC               | 1.584(RMSE)  | Lithium-Sulfur                 | 20°                              |
| Chmielewski, Adrian [49]| SoC               | 0.71%(MAE)   | Valve Regulated Lead Acid      | Room Temperature                 |

Generally, as the training epoch increases, the model’s accuracy and training time enhance. As illustrated in Figure 6, the MAEs quickly dropped in the initial few 500 epochs, then steadily decreased around 1200 epochs. Fluctuations were observed around 1300-2000 epochs, where MAEs suddenly increased then quickly stabilized. It means that the optimization algorithm hopped from one local optima to another. The training and the testing error reached a global minimum between 3000 to 4000 epochs. Hence, 3000 is a reasonable training epoch with localized optimal testing accuracy and an appropriate training time.

Figure 7 shows the prediction results of SoC by using BMS to measure the gel battery of a golf cart with LSTM, FNN, and RNN. The black line represents the results obtained through the coulomb count method. The red dotted line represents the prediction results obtained through LSTM. The blue dotted line and yellow line represent the prediction results through FNN and RNN. MAE between the coulomb count method and LSTM is 0.37%. MAE between coulomb count method to FNN and RNN is 2.8% and 1.7%, respectively. The results indicate that the gel battery has stable characteristics and can withstand temperature changes. Hence, the SoC of the gel battery can be precisely predicted by LSTM.

The generalization abilities of the designed LSTM model with different battery types are validated through the work of several other researches as seen in works [46]–[48] and summarized in Table 3. They include the MAEs for SoC, the battery types, and the temperatures. The SoC utilizes MAE equation to calculate the difference at each time point in each discharge process. The SoH also utilizes MAE to calculate the errors of the available capacity at the end of each discharge process. Almost all battery types were estimated with a 1% error or less, which shows that the LSTM Model is a promising candidate for various SoC or SoH estimations.

C. ANALYSIS OF SoH RESULTS

SoH is another important indicator for evaluating battery’s lifetime. It can be used to flexibly deploy the driving paths of golf carts. The predictions (LSTM) and measured (coulomb count) results from (1), (2), and (3) are indicated in Figure 8. It means that the prediction data are well fitted and indicate that the LSTM model has excellent prediction performance of the battery’s SoH on the testing data. From Figure 8, the SoH of the battery is dependent on temperature variations, especially since the measured data have changed significantly from ranges 125 to 180 cycles.

The loss calculation during the model’s training and evaluation has different implications. The loss function was used
TABLE 4. Top ten absolute errors in the 200 driving periods.

| Temperature (°C) | 42  | 38  | 35  | 45  | 37  | 40  | 32  | 22  | 17  | 32  |
|------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Driven Time      | 138 | 179 | 15  | 167 | 139 | 38  | 143 | 87  | 94  | 159 |
| Absolute Error (%) | 0.58 | 0.51 | 0.52 | 0.48 | 0.47 | 0.47 | 0.41 | 0.39 | 0.38 | 0.37 |

Figure 8. The differences of SoH between the experimental and predicted data for the tested battery. The red dotted line represents the measured value from the coulomb count method with (2) for each cycle. The blue line represents the prediction value from LSTM with (2). The yellow dotted line represents the average temperature for each cycle.

in the process of model building and the evaluation function was used to evaluate the completed model. Here, the MAE evaluates the SoH of the established model. The formula of MAE that evaluates prediction results in this work can be expressed as:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{pSoH_i - mSoH_i}{mSoH_i} \right| \cdot 100\% \quad (7)
\]

where \( n \) is the number of test samples and \( pSoH \) and \( mSoH \) are the predicted SoH and measured SoH of the battery system (recorded by a BMS), respectively.

Figure 9 illustrates that the absolute errors are within a very small range and the predicted SoH values are almost coincident with the actual values. Table 4 listed the top ten absolute errors in the 200 driving periods. It was observed that as the temperature changed drastically, the prediction error also increased. It means that the learning samples may not be enough and the LSTM model’s adaptability for temperature changes is still insufficient. Therefore, learning samples can be added to solve it.

D. THE BATTERY REPLACEMENT STRATEGY OF THE VEHICLE SERVICE MANAGEMENT CENTER (VSMC)

The VSMC (Chung Hsing University, Taiwan) has dozens of electric golf carts where the cost of replacing batteries is becoming a liability. This paper proposes an LSTM model that can estimate the characteristics of gel batteries as well as enhance the operations of the battery by monitoring, making the diagnosis, and providing control functions. The LSTM model provides accurate SoC and SoH as a guideline for golf carts to allocate the driving paths and areas. When the SoH of the battery is higher, it is dispatched to further paths, whereas when the SoH of the battery is lower, it is dispatched to shorter paths. As the number of batteries that need to be replaced reaches a certain number, they can be replaced in batches to reduce costs.

Based on sections 4.2 and 4.3, the VSMC model that allows for the cost of battery replacement is proposed. The model includes: reading the status of the battery on each golf cart, assigning the designated driving paths, and estimating the cost of battery replacement. The goal is to minimize the maintenance costs of golf carts and estimate the state of the battery through SoC and SoH with LSTM. In general, the batteries age differently as each golf cart takes different paths. Figure 10 illustrates three individual paths for the golf carts on the campus of Chung Hsing University. Each path starts from the charging station and is divided into levels 1, 2, and 3. Based on the differences in distance, recharging is not possible halfway; therefore, the SoH of the battery is used as the basis for assigning driving paths, as defined below:

1. Level 1: capacity is higher than 70% of rated capacity. Assign longer driving paths that are further away from the charging station.
2. Level 2: capacity is between 69% and 40% of rated capacity. Assign driving paths that are shorter than Level 1 and longer than Level 3.
3. Level 3: capacity is lower than 39% of rated capacity. Assign shorter driving paths that are closer to the charging station to avoid risks caused by insufficient battery level.
TABLE 5. The maintenance costs for a golf cart (provided by the manufacturer).

| Cost per task (USD) | Labor hour (f_lab) | Transportation allowance (f_ta) |
|---------------------|-------------------|-------------------------------|
| 4-series gel battery (f_bat) | 240              | 50                            | 200            |

To further explore the efficacy of the proposed model, the maintenance process of electric golf carts at the VMSC of Chung Hsin University is demonstrated in Table 5:

In the aspect of EV maintenance, Taiwan’s manufacturers not only charge fees for the batteries and working hours but also a transportation allowance (fixed fee per case). When comparing (8) and (9) with Table 4 as an example, where twenty golf carts (n_b = 20) required battery replacement at different times, 9,800 USD was yielded with (8) and 6,000 USD was yielded with (9). In contrast, the transportation allowance were lowered by 3,800 USD when batteries were replaced in batches.

As mentioned above, the strategy of replacing batteries in batches can significantly minimize the maintenance fee incurred by the manufacturers. The feasibility of this strategy greatly depends on the accurate estimation of SoC to adjust the vehicle’s driving paths and areas. Once a similar aging rate of the gel batteries is achieved, they can be replaced in batches to minimize costs.

V. CONCLUSION

The presented study is dedicated to the state of charge assessment and management of gel batteries. The recurrent neural network with the long short-term memory architecture model was first used to train for each battery to estimate the state of charge. A significant dataset was recorded with different batteries in different operating environments during 300 cycles.

The dataset was applied to the long short-term memory model training. The tested device consisted of a golf cart with four gel batteries. During the 200 drivings, the discharging characteristics and operating temperatures of the four batteries were collected through the battery management system and a computer. The verified results show that the proposed model displayed a mean absolute error of 0.376%. Long short-term memory aids in the state of charge estimations and aging mechanism investigations. Furthermore, the long short-term memory is easily implemented unlike the electrochemical model or equivalent circuit approaches.

Based on the experimental results of the golf cart with gel batteries, the proposed model can be fully integrated into a state-of-the-art monitoring system and provide an instant signal to track the remaining energy in the batteries. In this case, the reliability of the battery will be improved. In addition, the proposed model is scalable for other applications, such as energy storage for renewable energy while considering the same material design and technology.

Using the vehicle service management centers as an example, this paper proposes a management strategy that reduces maintenance costs by managing the driving path, adjusting the driving area, and replacing batteries in batches in order
to verify the accuracy and applicability of this model. The management strategy employs the state of charge and state of health of the gel battery calculations as key variables in assigning driving paths and areas for golf carts which yielded very satisfactory results. In addition, the proposed model is scalable for other applications, such as energy storage for renewable energy while considering the same material design and technology.

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