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Investigation of Battery Energy Storage System (BESS) during Loading Variation

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ABSTRACT

The data-driven Battery Management System (BMS) plays a crucial role in Electric Vehicles (EVs) and Battery Energy Storage Systems (BESS). EVs and energy storage systems utilize Lithium-ion (Li-ion) batteries due to their high energy density. However, recent concerns have arisen regarding the efficiency and reliability of Li-ion batteries, mainly due to issues of overheating and aging. Consequently, accurately predicting the State of Charge (SOC), State of Health (SOH), and degree of aging of the battery has become immensely important. This research focuses on analysing the accelerated loading effects on Li-ion batteries under various load conditions to gain insights into their performance under extreme mechanical stress. This paper also proposes a model employing a Feed-Forward Neural Network (FNN) to investigate the effects of fast-loading variations. The reliability testing of batteries involves monitoring their degree of aging through repeated charging or discharging cycles, facilitated by an IoT-based remote monitoring system. Experimental data was collected using the Neware BTS4000, a standard battery test equipment, and then validated with the FNN model, achieving a maximum accuracy of 99.9%.

1. Introduction

Growing climate concern has sparked a green energy revolution around the world, fueling a rapid worldwide transition away from fossil fuels to renewable energy [1]. Decentralized energy generation and distribution is the way of the future, and rechargeable batteries are the most cost-effective storage system [2-5]. Furthermore, for decades, electronic vehicles (EV) have increasingly replaced fossil fuel driven cars. However, due to the high maintenance costs of renewable energy storage systems (ESS) and EV batteries, the cost of renewable energy storage systems and electric car batteries remains a major problem in comparison to fossil fuel driven energy. A data-driven battery management system (BMS) is essential for safe, dependable, and optimal battery performance, which is critical for the green energy revolution to overcome the economic barrier.

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Lithium-ion (Li-ion) batteries are lighter, more efficient, and have a higher energy density than conventional batteries. Li-ion batteries are widely utilized in a wide range of applications, including as portable electronics such as smartphones, tablets, and laptops, hybrid cars, and energy storage systems [6]. Li-ion batteries' performance and reliability are becoming increasingly significant as they are employed in a wide range of applications. The operating circumstances of a battery have a considerable impact on its deterioration and lifetime [7]. As a result, it is critical to precisely anticipate battery lifespan in order to keep the battery in good condition [8]. State of Charge (SOC) estimation is critical for the safe and dependable operation of lithium-ion batteries, and it is one of the essential metrics in BMS that guarantees the battery is in good working condition in the event of overcharging or over-discharging [9,10]. IoT-based real-time monitoring of the battery's SOC, State of Health (SOH), overcharging, over-discharge, and capacity fading ensured the battery's safe and reliable operation.

Monitoring Li-ion battery capacity fading during many charging or discharging cycles under varied loads is a component of Li-ion battery reliability testing [11,12]. The data-driven battery management system assures reliable operation and timely maintenance, and it is critical for battery second-life applications that improve performance. To maintain the battery's optimum performance and lifetime, the data acquired from battery testing must be carefully analyzed [13].

In the past, several machine learning (ML) and deep learning (DL) methods were used for accurately predicting battery characteristics during loading instances [14-16]. Load distinction during charging and discharging produces an ambiguous nature in the battery data. Artificial neural network (ANN) training has been demonstrated to be more effective because of its superior generalization capabilities [17]. In this paper, a feed-forward neural network (FNN) approach is applied to investigate the loading effect on Li-ion batteries to accomplish a rapid SOC prediction. FNN network training period is faster due to the simple structure of the network compared to the recurrent neural network (RNN) or convolutional neural network (CNN) [18].

2. Methodology

In this experiment, constant current charge (CC-Chg.) and constant current discharge (CC-DChg) modes are preferential to constant current voltage charge (CCV-Chg) and constant current voltage discharge (CCV-DChg) modes because constant current voltage charge deteriorates the battery cell and shortens the battery's lifespan [19]. The mode of test should be determined when conducting the test. The battery will be charged, rested, and discharged multiple times until the maximum number of cycles is reached. Li-ion batteries have a maximum charge voltage of 4.2V and a minimum discharge voltage of 2.5V. The charging limit is 4.2V, while the discharging limit is 3V. Figure 1 shows the flowchart for the battery test. Lowering the discharge voltage to 2.5V would have an impact on the battery's longevity and performance. The charging and discharging current rate (C-Rate) are modified after determining the required C-Rate. In the event of an unforeseen disturbance during the experiment, the charge and discharge times are set to be longer than the C-Rate calculated times. Because Li-ion batteries are extremely sensitive to voltage changes, the protective limitations have been devised to prevent them from being discharged below 2.5 volts or charged above 4.3 volts. The BMS contains a battery monitoring system as one of its important components to ensure the battery's secure and reliable operation. Battery parameters such as SOC and SOH are remotely monitored via apps to ensure safe and reliable battery testing. After the battery test, the data is retrieved and imported to MATLAB for battery SOC prediction with ANN.

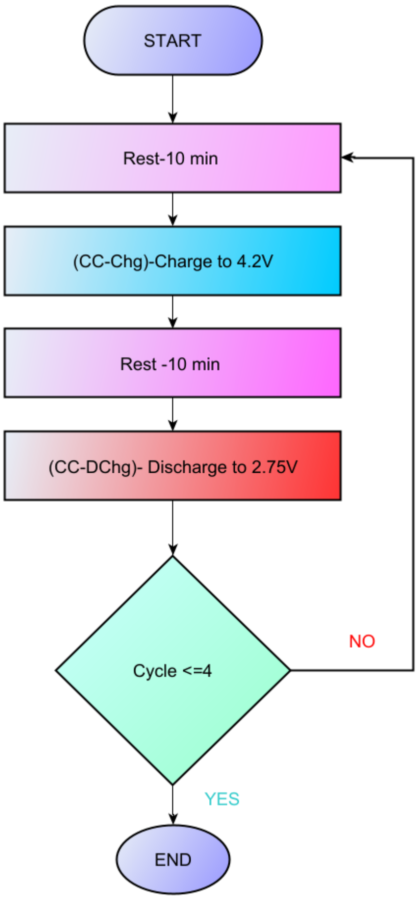

Fig. 1. Flowchart of Li-ion battery test for 4 cycles

Subsequently, the ANN technique is used to investigate the energy storage system. FNN consists of up of three layers: input, hidden, and output [20]. Feed-forward networks are commonly used in time series prediction to verify the accuracy of SOC prediction at different charge-discharge rates. As a data-driven approach is used, SOC estimation is dependent on input and output factors [21]. The input parameters of the FNN network in data-driven techniques are time, current, and voltage, while the output parameter for SOC prediction is capacity.

The FNN network learns battery behaviors based on input and output parameters. The capacity is the scalar element in this model, and the time, current, and voltage of the battery serve as vector inputs to the FNN. The vectors of input are expressed mathematically as φ_k= [T_k, I_k , V_k], where T_k,I_k and V_k denote time, current, and voltage at time step k. The capacity is denoted by φ_o=soc_k.

Figure 2 depicts how input vector parameters are fetched into the input layer in order to estimate soc_k. Figure 2 depicts the architecture of the FNN model, where time, current, and voltage are inputs and capacity are output.

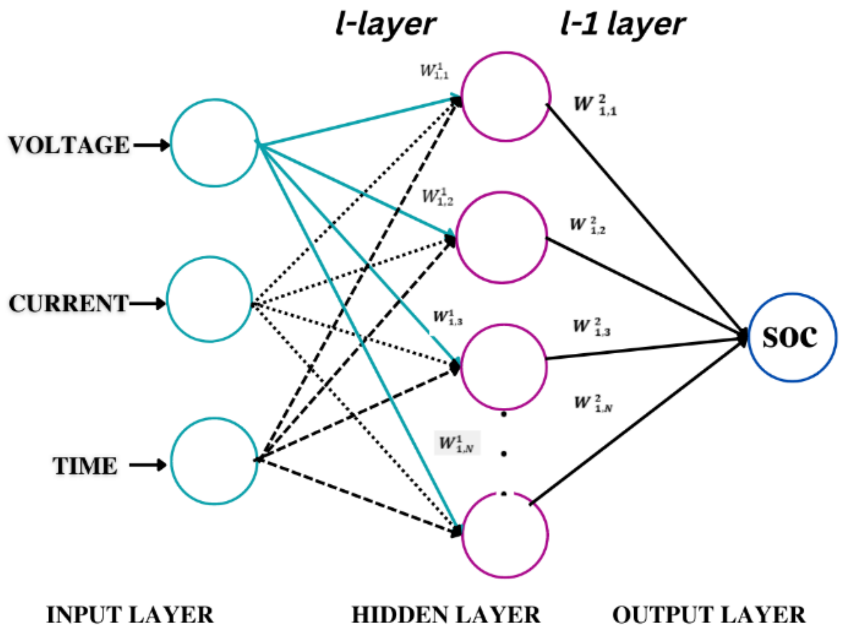

Fig. 2. FNN SOC prediction model. The input data are identified by $\varphi_k = [T_k, I_k, V_k]$, where $T_k, I_k,$ and V_k represent the time, current and the voltage at time-step k. The estimated SOC $\varphi_o = SOC_k$ is the output of the FNN at each time step k.

The sigmoid activation function used in the FNN network:

$$\sigma(k) = \frac{1}{1+e^{-k}} \quad (1)$$

In this model, Rectified Linear Unit (ReLu) nonlinearity is utilized for smooth training process. ReLu function is calculated as,

$$\sigma = \max(0, k) \quad (2)$$

In the network, the data separated into 3 categories such training (60%), testing (20%), and validation (20%). The hidden layer, learning rates (alpha), and decay factor (beta) are adjusted through hyperparameter optimization (HPO) until the optimum training performance is obtained. The performance metrics of mean-squared error (MSE), mean average error (MAE), and root-mean-squared error (RMSE) are used to evaluate the performance of the SOC prediction with FNN network. The performance metrics are calculated as follows,

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}(\mathrm{SOC}_k - \mathrm{SOC}_k^*)^2 \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\mathrm{SOC}_f - \mathrm{SOC}_k^*\right)^2} \quad (4)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}(|\mathrm{SOC}_k - \mathrm{SOC}_k^*|) \quad (5)$$

where, the size of sample data N, the estimated SOC denoted as SOC_K with FNN network, and experimental data denoted as SOC_k^*.

2.1 Battery Specification

The A18650 Li-ion battery cell model was used for the standard battery testing. Table 1 shows the specifications of a Li-ion battery with a nominal capacity of 2600mAh, a maximum voltage of 4.2V, and a minimum voltage of 2.5V.

Table 1
Battery specification of Li-ion 2600mAh battery

Parameter	Specification
Cell Voltage	3.7V
Nominal Capacity	2600mAh
Maximum Voltage	4.2V
Minimum Voltage	2.5V
Energy	8.4Wh
Size	18.3mm x 69.5mm

2.2 Battery Specification

Battery testing bench set up with a Neware battery testing system (BTS4000), a host computer, a safety perimeter, an air conditioner, and internet access. During the charge and discharge cycles, the battery is tested at room temperature (25°$\pm$4) and monitored in real-time using IOT application. The battery test bench is depicted in Figure 3.

Fig. 3. Test bench for battery cell testing compromised of BTS400, PC, and internet access

3. Result and discussion

3.1 Loading Effect Analysis on Li-ion Batteries during Charging

Mechanical stress on the battery is reduced at steady charge (0.4C); as a result, the battery's initial voltage has surged to just 3.4V, with the slight degree of capacity loss seen in Figure 4. The graph shows that a 0.4C-rate, slow-charging Li-ion battery cell has the potential to store 2350mAh more than its stated capacity (2600mAh). The SOC at 0.4C-Rate is 90.56%, meaning that 90.56% of the battery's capacity is available with 0.4C-Rate charging. Because of mechanical stress and internal resistance, the initial voltage has grown to 3.5V at 0.8C, which is somewhat higher than at 0.4C, which has a reduced capacity fading relative to its rated capacity. According to the graph in Figure 4, a Li-ion battery with a moderate charging rate (0.8C-Rate) can store 2301mAh more than its nominal capacity (2600mAh). The SOC with (0.8C-Rate) charging is 88.5%, showing that (0.8C-Rate) charging causes slow aging. Charge capacity has decreased marginally when C-Rate has increased. As the C-rate increases to 1.2C, the battery's initial voltage rises to 3.6V due to increased mechanical stress and internal resistance, as seen in Figure 4. A larger resistance limits ion transfer, resulting in capacity loss. The Li-ion battery has consumed 2174mAh less than its rated capacity (2600mAh) as shown in the graph, and the SOC at (1.2C-Rate) is 83.6%, which is not an optimal capacity for a battery. As a result, a rise in C-Rate above the rated capacity of the battery causes capacity degradation and battery aging. As a result, raising the C-rate causes the battery to degrade faster, as shown in Figure 4, and charging above the standard C-rate accelerates battery aging. As a result, charging at a faster rate will reduce the cyclability of a Li-ion battery. The ideal C-Rate is 0.8C, at which 90% of the capacity may be stored at a low charging rate with a long cycle performance forecast.

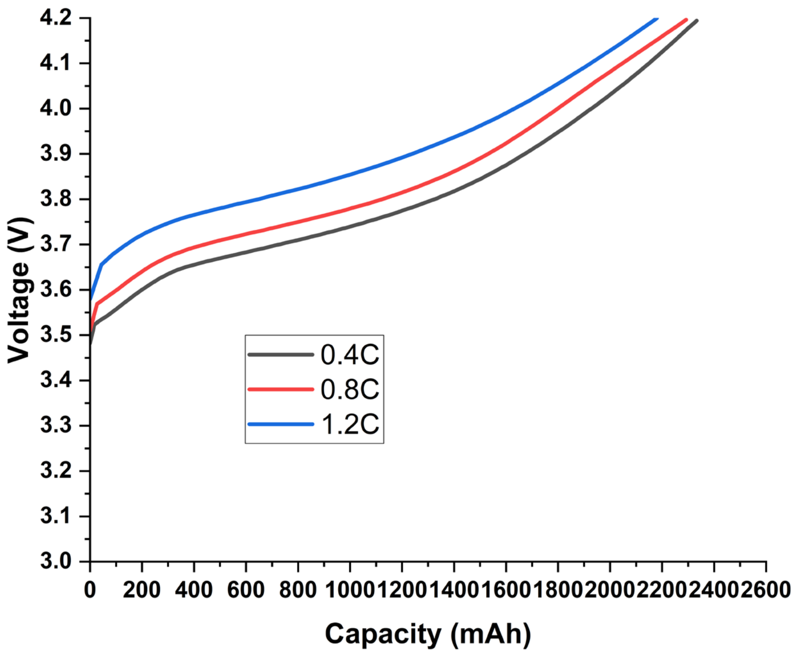

Fig. 4. Loading variation on the battery energy storage system is investigated on 3 separate charge rates: 0.4C, 0.8C and 1.2C

3.2 Loading Effect Analysis on Li-ion Batteries during Discharging

Discharging at 0.8C-rate has resulted in a minor loss in discharge capacity due to mechanical stress and internal resistance as shown in Figure 5. At 0.8C, a Li-ion battery can extract 2373mAh, or

91.3% of its rated capacity (2600mAh). A quick discharge at 1.1C reduces the battery's starting voltage (V) to 4.1V due to increased mechanical stress and internal resistance induced by draining faster than the C-rate, as shown in Figure 5. Due to the quick discharge rate (2600mAh), the Li-ion battery can only withdraw 2304mAh, or 88.6% of its rated capacity. As a result, if the C-rate is surpassed, the performance of a Li-ion battery suffers greatly.

Rapid discharging at 1.4C-rate causes a reduction in initial voltage (V) to 3.9V, increases in C-rate cause the battery's mechanical stress and internal resistance to rise, resulting in another drop in initial voltage and a commensurate loss of capacity, as shown in Figure 5. A Li-ion battery could clearly only supply 2172mAh, or 83.5% of its advertised capacity. Discharging faster than its normal C-rate reduces its performance dramatically. As a result, draining a Li-ion battery at a rate greater than the conventional C-Rate causes the battery to degrade more faster than usual. One of the most significant downsides of li-ion batteries is their tendency to overheat and degrade when subjected to high C-rates [22]. Increasing the discharge rate, particularly over the C-rate, is related with a deterioration in battery performance, as evidenced by the depth of discharge (DoD) declining by 91.3%, 88.6%, and 83.5%, respectively. Performance analysis have found that the optimum discharge rate of Li-ion battery in ESS is 0.8C. As a result, loading variation within 0.8 C-rate would be ideal for battery energy storage system (BESS).

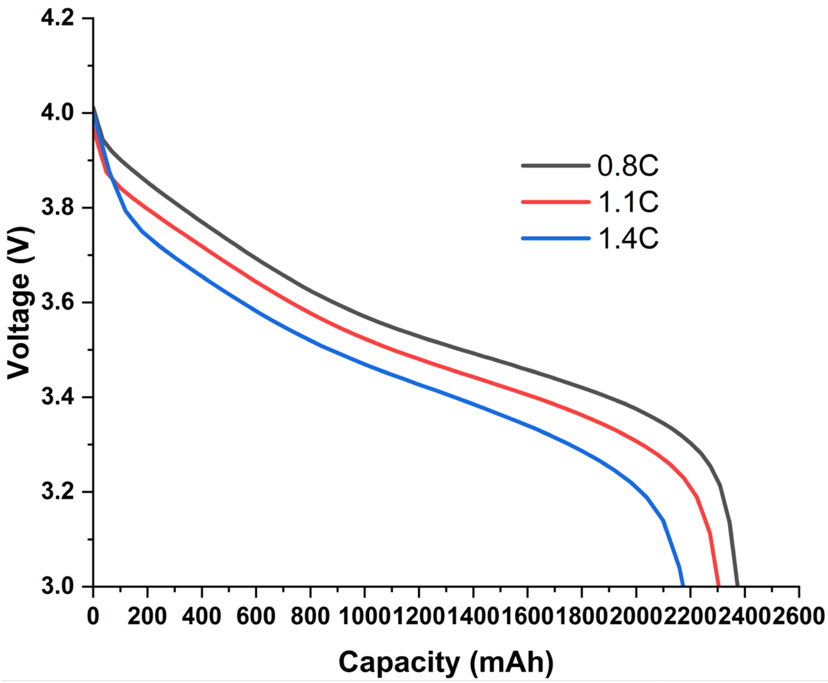

Fig. 5. Loading variation on the battery energy storage system is investigated on 3 separate discharge rates: 0.8C, 0.1C and 1.4C

3.3 Feed-Forward Neural Network SOC Estimation Performance Analysis

The number of hidden layers is determined by the performance measures with the lowest error MSE, MAE, and RMSE. The hidden layers are adjusted until maximum accuracy in SOC prediction is attained. The optimal number of hidden layers for SOC selection was discovered during hyper-parameter optimization to be '5'. As a result, the SOC prediction model is created with a fixed number of hidden layers of '5', a learning rate of $\alpha = 10^{-3}$, and a decay factor of $\beta = 0.8$. The model's performance is then evaluated using three different charge and discharge rates. Figure 6 shows the prediction accuracy of the constructed SOC model at various charge rates. Where the inaccuracy grows with increasing charge rates because increasing charge rates reduces the size of the data. As a result, the model's performance is superior while fetching big amounts of data. As data sizes shrink, the model appears to have more generalization errors. Despite this, the SOC prediction model performs admirably due to minor mistakes.

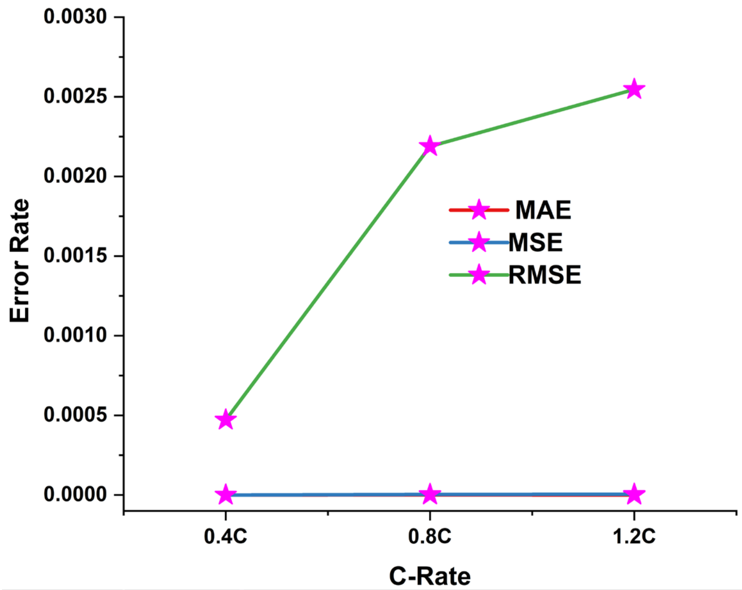

Fig. 6. The performance of FNN network at 3 separate charging rates: 0.4C,0.8C, and 1.2C. Where the performance of the model is evaluated based on MSE, MAE, and RMSE

On the other hand, the SOC prediction model is then evaluated on three different discharge rates: 0.8C, 1.1C, and 1.4C to investigate the model's capacity to grasp and analyse different modes of data. The model's test performance is depicted in Figure 7, where errors grow as C-rates increase. The performance trend for both charge and discharge data is similar, with small variations. Furthermore, because ANN has increased generalization effect when the data includes specific feature or symbol, the mistake rates are considerably lower at varied discharge rates compared to the charges rates.

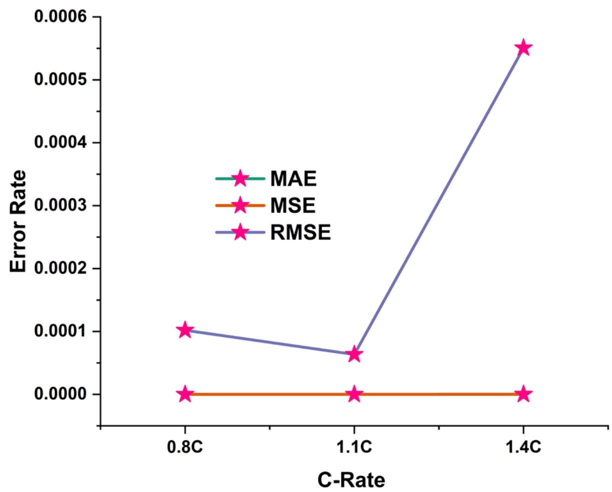

Fig. 7. The performance of FNN network at 3 separate discharging rates: 0.8C,1.1C, and 1.4C. Where the performance of the model is evaluated based on MSE, MAE, and RMSE

3.4 Monitoring Battery Parameter

Li-ion batteries have faulty (SOC) and overheating issues, which need real-time monitoring of the battery to ensure safe and reliable operation [23]. As a result, an IoT-based remote monitoring system is built during the battery test to monitor test conditions via Team Viewer, as shown in Figure 8 and 9.

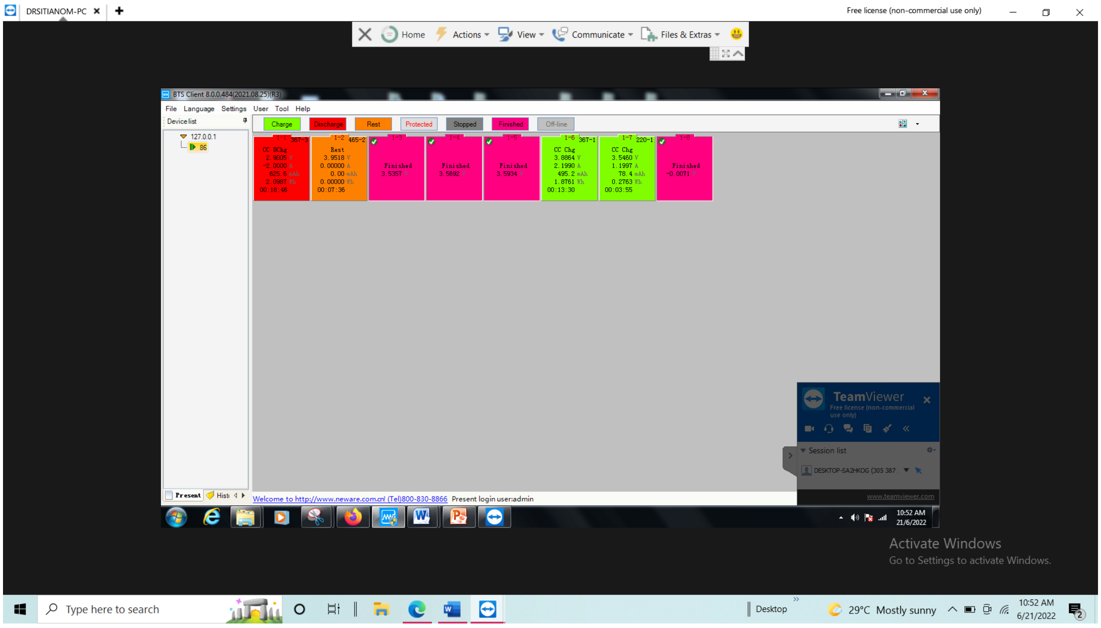

Fig. 8. Battery parameter such as the SOC and SOH monitored remotely online

The battery monitoring system includes test monitoring, on/off control, and building testing. Remote monitoring of battery parameters such as SOC, SOH, and capacity fade. The remote monitoring system enabled the safe and reliable operation of the battery test.

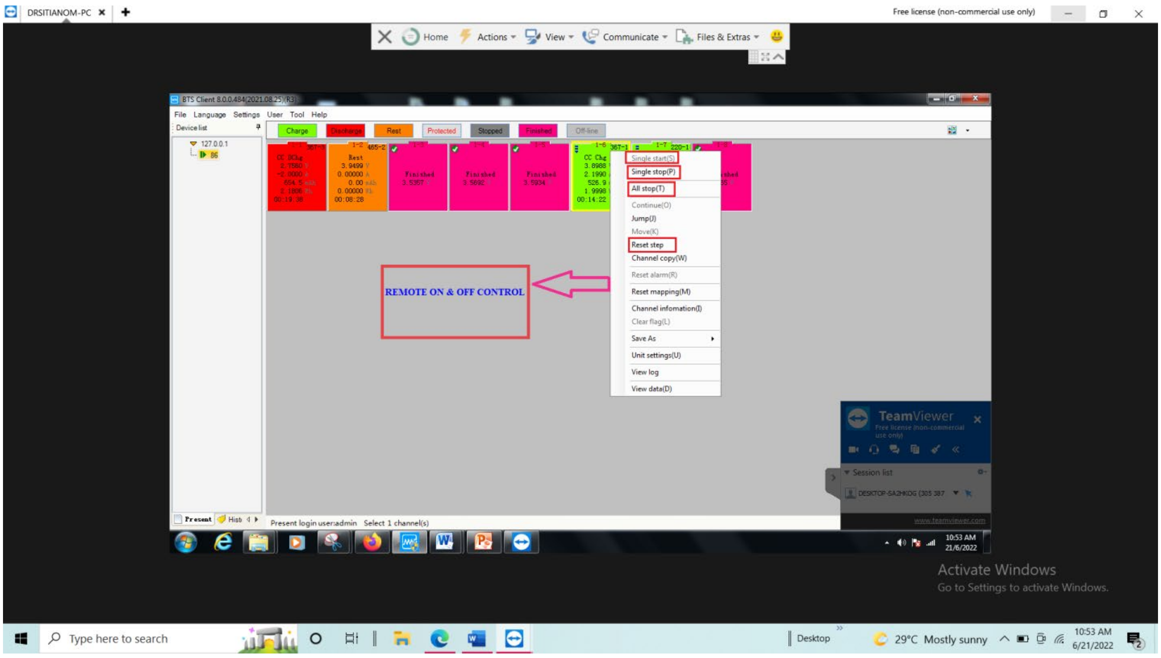

Fig. 9. Remote battery test on and off control in case of overcharging

4. Conclusions

In conclusion, this study conducted tests on Li-ion batteries at various charge and discharge rates to investigate the effects of loading deviations on energy storage systems. Three charge rates (0.4C, 0.8C, and 1.2C) and three discharge rates (0.8C, 1.1C, and 1.4C) were examined. The results revealed that typical C-rate loading gradually ages the battery but also provides potential for a second life. Additionally, this research addressed the consequences of exceeding the standard C-rate. An optimal moderate charge and discharge rate were identified based on the investigation of exceeding the conventional C-rate. Furthermore, a feed-forward neural network (FNN) model was utilized to accurately predict the State of Charge (SOC) during loading variations. The FNN model exhibited high accuracy, achieving an SOC estimation accuracy of 99.99%. This research contributes valuable insights into optimizing loading conditions and utilizing FNN models for precise SOC prediction in energy storage systems.

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