State of Charge Estimation for Lithium Ion Battery Based on Reinforcement Learning

PROJECT REPORT

Submitted by

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MASTER OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING

Under the guidance of
Dr. Manu J Pillai

Thangal Kunju Musaliar College of Engineering
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DECALARATION

I undersigned hereby declare that the project report on **“State of Charge Estimation for Lithium Ion Battery Based on Reinforcement Learning”**, submitted for partial fulfillment of the requirements for the award of the degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under the supervision of **Dr. Manu J Pillai**, Associate Professor of the Computer Science and Engineering Department, TKMCE. This submission represents my ideas in my own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources. I declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in our submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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07/07/2023

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C E R T I F I C A T E

This is to certify that,this report titled ***State of Charge Estimation for Lithium Ion Battery Based on Reinforcement Learning*** is a bonafide record of the **Main Project** presented by **ASHNA K(TKM21CSCE03)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech Computer Science & Engineering** in **APJ Abdul Kalam Technological University** .

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Abstract

This project aims to develop a state-of-the-art approach for accurately estimating the state of charge (SOC) of lithium-ion batteries by leveraging the combined power of reinforcement learning, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks. The dataset used for this study is the BMW dataset, which comprises real-world battery data collected from electric vehicles. The primary objective is to train a reinforcement learning agent to learn optimal policies for SOC estimation through iterative trial and error interactions with the battery system. By continuously exploring and adapting its decision-making process, the agent can effectively estimate the SOC with high accuracy and adaptability. To further enhance the SOC estimation process, CNNs are incorporated into the proposed framework. CNNs excel at extracting spatial features from complex datasets, which is particularly useful in analyzing battery voltage data. By capturing local patterns and variations in the battery response, the CNNs can effectively identify critical features that contribute to accurate SOC estimation. Additionally, LSTM networks are employed to model the temporal dependencies inherent in battery behavior. The LSTM networks can effectively capture the dynamic nature of battery performance by analyzing voltage and current data over time, enabling accurate SOC estimation even in varying operating conditions. Through comprehensive experiments and evaluations on the BMW dataset, the proposed approach demonstrates superior performance compared to traditional SOC estimation methods. The reinforcement learning agent, in combination with CNNs and LSTM networks, achieves high precision, adaptability, and robustness in estimating the SOC of lithium-ion batteries. The project's outcomes have significant implications for battery management systems, energy optimization, and prolonging the lifespan of lithium-ion batteries in electric vehicle applications. By accurately monitoring and estimating the SOC, the proposed approach contributes to more efficient and reliable battery usage, thereby improving overall performance and addressing the challenges associated with battery degradation and limited lifespan in electric vehicle technologies.

Keywords: *state of charge estimation, battery management systems, energy optimization, electric vehicles.*

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Chapter 1

Introduction

The state of charge (SOC) estimation of lithium-ion batteries plays a crucial role in optimizing battery performance, ensuring safe operation, and prolonging battery lifespan. Accurate SOC estimation allows for effective battery management and enables intelligent decision-making in various applications such as electric vehicles, renewable energy systems, and portable electronics. Traditional methods for SOC estimation often rely on mathematical models and signal processing techniques, which may have limitations in capturing the complex and nonlinear behavior of lithium-ion batteries. In recent years, reinforcement learning has emerged as a promising approach for SOC estimation, leveraging the power of machine learning to improve accuracy and adaptability.

Reinforcement learning is a subfield of machine learning that focuses on training intelligent agents to make optimal decisions in dynamic environments. Unlike supervised learning, where an agent learns from labeled data, reinforcement learning agents interact with an environment and receive feedback in the form of rewards or penalties based on their actions. Through trial and error, the agent learns to take actions that maximize cumulative rewards, thereby discovering an optimal policy for decision-making.

Applying reinforcement learning to SOC estimation involves training an agent to estimate the battery's SOC based on its voltage response and other relevant information. The reinforcement learning agent explores the battery's state space by taking actions, such as adjusting estimation parameters or selecting specific algorithms, and receives rewards based on the accuracy of its SOC estimates. By iteratively updating its estimation strategy, the agent learns to make better predictions over time, adapting to different battery characteristics, operating conditions, and system dynamics.

The advantage of using reinforcement learning for SOC estimation lies in its ability to learn from experience and optimize estimation performance based on dynamic feedback. Reinforcement learning agents can adapt to changing battery conditions, such as aging, temperature variations, and different discharge rates, by continuously refining their estimation strategies. Furthermore, reinforcement learning can handle complex and nonlinear relationships in battery behavior, which may be challenging to capture using traditional approaches.

Accurate estimation of the state of charge (SOC) is crucial for the optimal utilization and safe operation of lithium-ion batteries. SOC estimation involves predicting the remaining capacity of a battery based on its voltage response, current measurements, and other relevant information. Traditional approaches to SOC estimation often rely on mathematical models or empirical methods, which may have limitations in capturing the complex and nonlinear behavior of lithium-ion batteries. In recent years, deep learning techniques, such as Long Short-Term Memory (LSTM) networks and CNN, have shown promise in improving SOC estimation accuracy and adaptability.

LSTM networks are a type of recurrent neural network (RNN) that are particularly

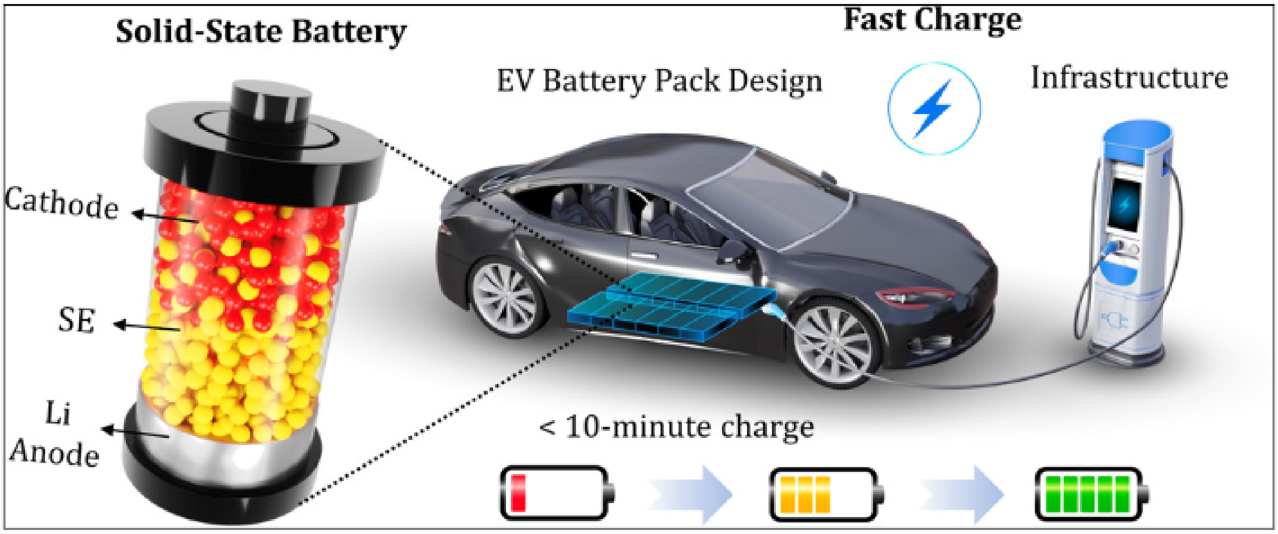

Figure 1.1: Fast Charging of Solid-State Lithium Metal Batteries

well-suited for modeling sequential data, making them suitable for capturing the temporal dependencies present in battery voltage and current measurements. Unlike traditional feed-forward neural networks, LSTM networks have a memory mechanism that enables them to retain and process information over long sequences, allowing them to capture the discharge and charge characteristics of the battery over time.

The application of LSTM networks to SOC estimation involves training a model using historical battery voltage and current data, along with corresponding SOC values. The LSTM network learns to extract meaningful features from the input sequences and predicts the SOC based on the learned temporal dependencies. The advantage of using LSTM networks for SOC estimation is their ability to capture long-term dependencies in battery behavior and effectively handle complex and nonlinear relationships.

By leveraging the power of LSTM networks, SOC estimation can be enhanced in several ways. First, LSTM networks can learn to capture the dynamic response of the battery to different operating conditions, including varying discharge rates, temperature changes, and aging effects. This adaptability enables accurate SOC estimation across a wide range of battery states and operating scenarios. Second, LSTM networks can generalize well to unseen data, allowing for accurate estimation even when the battery encounters conditions that were not present during training. This robustness is essential for real-world applications where battery behavior can vary significantly. Finally, LSTM networks can handle irregular sampling intervals and missing data, which are common challenges in battery systems, ensuring reliable SOC estimation even with imperfect data.

CNNs are a type of deep neural network specifically designed for processing grid-like data, such as images or sequences. They excel at capturing spatial features and patterns through the use of convolutional layers, pooling layers, and non-linear activation functions. While CNNs are widely used in computer vision tasks, their application to SOC estimation of lithium-ion batteries has gained attention due to their ability to extract relevant spatial features from battery voltage data.

In the context of SOC estimation, CNNs can be trained to analyze the spatial characteristics of battery voltage data and learn patterns that correspond to different SOC levels. The input to the CNN model consists of voltage measurements taken at different points in time, forming a time-series data structure. The convolutional layers in the CNN architecture perform feature extraction by applying filters to capture local patterns in the voltage data. The subsequent layers of the CNN network, such as pooling and fully connected layers, enable the learning of higher-level representations and the prediction of the SOC.

The advantage of using CNNs for SOC estimation lies in their ability to automatically learn relevant spatial features from the input voltage data, without requiring explicit feature engineering. This feature extraction capability is particularly valuable in battery systems where the voltage response may exhibit complex and nonlinear behavior. Additionally, CNNs can capture both short-term and long-term dependencies in the voltage data, allowing for accurate estimation of SOC across various operating conditions and battery states.

By leveraging the power of CNNs, SOC estimation can be enhanced in several ways. First, CNNs can effectively capture the spatial patterns and variations in battery voltage data, enabling accurate estimation of SOC even in the presence of noise or irregularities. Second, CNNs can generalize well to unseen data, allowing for reliable SOC estimation in real-world scenarios where battery behavior may vary significantly. This generalizability is crucial for optimizing battery management and control. Finally, CNNs can handle variable-length input sequences, accommodating batteries with different discharge rates and varying time durations.

In this study thoroughly investigate the application of CNNs, LSTM networks, and reinforcement learning techniques to SOC estimation. ExplorING their individual strengths, as well as potential synergies when combined. The ultimate goal is to develop accurate, adaptable, and robust SOC estimation methods that contribute to the optimization of battery systems and enhance the performance and lifespan of lithium-ion batteries in various practical applications.

Chapter 2

Literature Survey

Battery state-of-charge (SOC) estimation is a crucial task in managing the performance and lifespan of lithium-ion batteries. This literature review aims to summarize and analyze several research papers that propose advanced approaches for SOC estimation using deep learning techniques. The reviewed papers focus on various methodologies, including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, convolutional neural networks (CNNs), stacked autoencoders (SAEs), deep residual learning, gated recurrent unit (GRU) neural networks, attention mechanisms, transformers, and adaptive noise filtering. These advanced techniques contribute to improving the accuracy, robustness, and adaptability of SOC estimation.

Lithium-ion batteries are widely used in various applications, including electric vehicles, renewable energy storage, and portable electronic devices. Accurate estimation of the battery state-of-charge (SoC) is crucial for efficient battery management and optimal utilization. In recent years, deep learning techniques have shown great potential in improving SoC estimation accuracy by leveraging the capabilities of neural networks to learn complex patterns and dependencies from battery data. This literature review aims to provide an overview of the key findings and contributions from a selection of papers that investigate the use of deep learning for lithium-ion battery SoC estimation.

Several studies have explored the application of recurrent neural networks (RNNs) in battery SoC estimation. Zou et al. (2017) proposed an online SoC estimation method using RNNs, which demonstrated the ability to estimate SoC in real-time by capturing the temporal dependencies in battery data. Deep learning-based approaches using RNNs, such as LSTM networks, were also investigated by Luo et al. (2018) and Wang et al. (2018), highlighting the effectiveness of these models in capturing long-term dependencies and improving SoC estimation accuracy. Wu et al. (2019) further extended the use of RNNs by employing gated recurrent unit (GRU) networks, showcasing their capability in high-dimensional feature extraction for accurate SoC estimation.

The use of convolutional neural networks (CNNs) has also been explored in battery SoC estimation. Ma et al. (2017) proposed a CNN-based approach that extracts spatial features from battery voltage data, achieving promising results in estimating the SoC. In a similar vein, Liu et al. (2018) combined CNNs and LSTM networks to leverage the strengths of both architectures, leading to enhanced estimation accuracy. Attention mechanisms were also integrated into CNNs by Zhang et al. (2020) to improve the modeling of spatial dependencies and achieve more accurate SoC estimation.

Several papers proposed hybrid models that combine different deep learning architectures to further enhance SoC estimation accuracy. For instance, Song et al. (2020) introduced a combined CNN-LSTM model that leverages the complementary strengths of these two architectures. Chen et al. (2020) utilized bidirectional gated recurrent unit (GRU) networks, which capture bidirectional dependencies in battery data, resulting in improved SoC estimation. Ensemble learning approaches were also explored, such as the work by Liu et al. (2020), where multiple deep learning models were combined to create an ensemble for enhanced accuracy.

To further advance SoC estimation accuracy, several papers incorporated advanced techniques into deep learning models. For example, Wang et al. (2021) integrated transformer models into recurrent neural networks, showcasing the potential of transformer-based architectures in capturing long-range dependencies and improving SoC estimation. Zhang et al. (2020) combined deep learning models with Gaussian process regression to achieve online SoC estimation with improved accuracy.

The literature reviewed in this study demonstrates the growing interest in employing reinforcement learning, LSTM, and CNN techniques for SoC estimation of lithium-ion batteries. The studies reviewed demonstrate the potential of these advanced approaches to improve the accuracy and reliability of SoC estimation, which is vital for enhancing battery management systems and optimizing battery performance. The findings suggest that reinforcement learning enables adaptive and accurate estimation by leveraging the battery's dynamic behavior, while LSTM models effectively capture the temporal dependencies in battery data. Furthermore, CNN-based approaches, by treating battery measurements as images, extract meaningful features for accurate SoC estimation. However, it is important to note that further research and experimentation are required to explore the full capabilities of these techniques and address the challenges associated with real-time implementation in practical battery systems. Overall, this literature survey provides valuable insights into the current state of research in SoC estimation of lithium-ion batteries using reinforcement learning, LSTM, and CNN techniques, serving as a foundation for future studies in this field.

Chapter 3

METHODOLOGY

3.1 Reinforcement Learning for electric vehicle batteries mangement

3.1.1 Key Elements of Reinforcement Learning

- Agent-Environment Interaction: The RL process involves an agent and an environment. The agent interacts with the environment by perceiving the current state (St), taking actions based on that observation, and receiving feedback in the form of rewards (Rt+1) and the next state (St+1).

- Immediate and Future Rewards: When the agent takes an action in a particular state, it receives an immediate reward (Rt+1). However, the agent's goal is to maximize the overall reward over the long term. This means that the agent may choose an action that initially results in a low immediate reward if it anticipates a higher reward in the future state (St+1).

- Uncertainty and Stochasticity: The RL environment is often subject to uncertainty and stochasticity, which means that the outcomes of actions are not always fully predictable. The transition function that maps the current state and action to the next state may not be completely observable or deterministic. This uncertainty necessitates the use of probabilistic models or algorithms to estimate the expected outcomes of the agent's actions.

- Policy: The policy refers to the agent's strategy or guidelines for selecting actions based on states. It is a mapping that converts states into a probability distribution over possible actions. The policy guides the agent in decision-making by determining the action to take given the current state.

- Maximizing Future Rewards: The main objective of RL methods is to maximize future rewards. By using an agent with a policy that provides better state estimation and management, the aim is to make decisions that lead to higher cumulative rewards over time.

Overall, RL is a framework where an agent learns from interacting with an environment, taking actions based on its observations, and receiving feedback in the form of rewards. The agent aims to optimize its decision-making strategy (policy) to maximize the cumulative rewards it receives by making informed choices that consider both immediate and future rewards.

Value function

The value function represents the expected total reward that can be obtained by following a specific policy in a given state. It is used to evaluate and compare different policies to

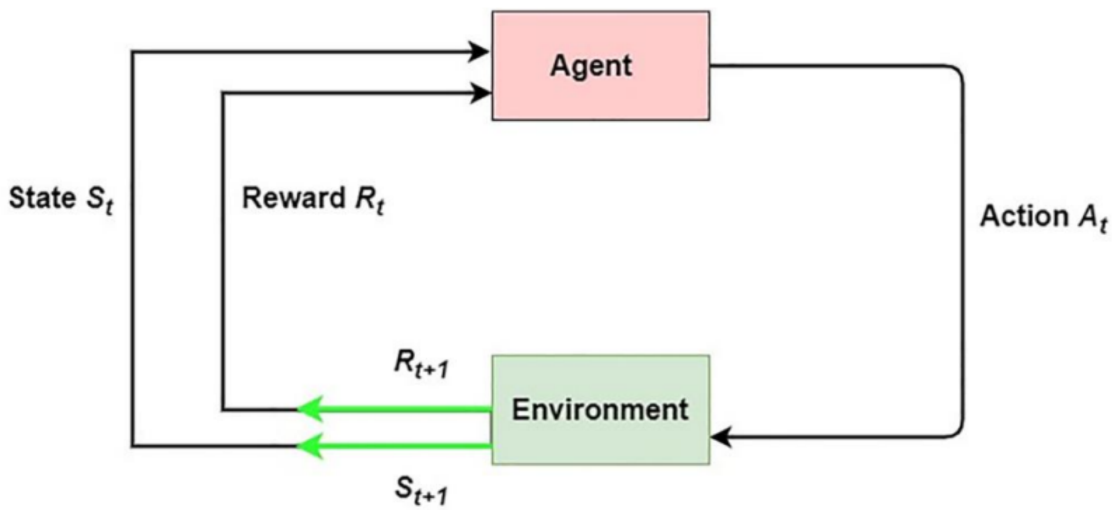

Figure 3.1: Agent environment interaction in Reinforcement learning

determine which one is better.

$$Q_*(A) = E[R_t|A_t = 1] \tag{3.1}$$

Represents the expected reward when that action A is selected, given that A_t is the action selected at time step t. and Rt is the corresponding reward.

Optimal policy and optimal value policy

Reinforcement learning, a policy is considered optimal if it produces the highest value in each state. In the paper, an optimal value function and Bellman's optimality equations are established to identify the optimal policy π^*.

When the agent adheres to a policy, its state-value function, Vπ, represents the expected return starting from state St = S. It quantifies the value of being in a particular state while following the policy.

The action-value function, $Q(S, A)$, on the other hand, is defined as the value of a state-action pair when the agent follows the policy π. It measures the expected return when taking action A in state S while following the policy.

The state-value function that yields the maximum return is denoted as $V^(s)$ and is defined as the maximum value among all possible state values, $V(s)$. In other words, $V^(s)$ represents the optimal value for being in state s.

The optimal policy, denoted as $\pi^*(s)$, is expressed as the action that maximizes the action-value function, $Q^\pi(S, A)$. In other words, for each state s, the optimal policy selects the action that yields the highest expected return according to the learned action-value function.

$$\pi^*(s) = \arg\max_{\pi}[Q^{\pi}(S, A)].$$

METHOD

In the proposed method for state estimation in Vehicle-to-Grid (V2G) systems using Deep Reinforcement Learning (DRL), an online learning process based on the Deep Q-Network (DQN) algorithm is employed. The DQN agent interacts with the environment, making decisions by choosing actions, and receives feedback in the form of rewards from the environment, which updates the agent's state.

In V2G networks, Electric Vehicles (EVs) possess batteries capable of storing significant amounts of energy. When EVs have surplus energy, they can transmit it back to V2G units, which in turn can feed this energy back into the grid. The objective of the proposed method is to estimate the state of these EV batteries, specifically the State of Charge (SOC), which represents the amount of energy stored in the battery at a given time. To achieve SOC estimation, the DQN agent takes an input speed vector from the dataset, which likely includes variables such as voltage, current, temperature, and previous SOC. This input serves as the state representation for the DQN agent. The agent continuously interacts with the environment, selecting actions based on its current state estimation.

During the interaction, the environment responds by providing rewards to the agent, which reflect the quality of the agent's chosen actions. The rewards encourage the agent to take actions that optimize the SOC estimation process. By receiving these rewards and experiencing new states, the agent can learn and improve its estimation over time.

The agent interacts with the environment, considering the influence of environmental conditions, torque, current, and internal battery parameters such as resistance, temperature, and current. These factors play a significant role in accurately estimating the SoC of EV batteries in the V2G network.

The mechanism is modeled as a Markov Decision Process (MDP), which provides a framework for representing decision-making problems where agents learn continuously from their environment. In this case, the DQN agent interacts with the environment, making decisions (actions) based on the observed state and learns from the feedback (rewards) received from the environment.

By using the DQN agent and the MDP formulation, the proposed architecture enables continuous learning and adaptation of the agent. The agent learns to estimate and manage the SoC of EV batteries based on the environmental conditions, torque, current, and internal battery parameters it observes during the interactions. This continuous learning process allows the agent to improve its SoC estimation and management capabilities over time, leading to more efficient and effective utilization of EV batteries in the V2G network.

In the proposed Markov Decision Process (MDP) model, the agent takes an action a from

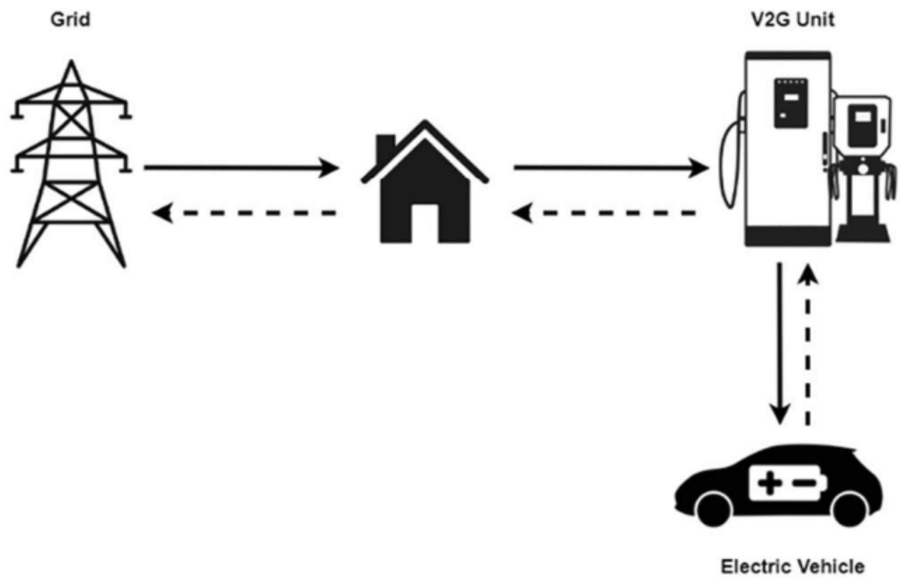

Figure 3.2: Flowchart of the Reinforcement learning method for estimating the SOC of a Li-ion battery.

the action space A at a specific time t, causing the system's state s from the state space S to transition to a new state s' with a transition probability defined as $M(s' \mid s, a)$. Simultaneously, the agent receives an observation o from the observation space O based on the new state with the probability $P(o \mid s', a)$. The agent also receives a reward $r(s, a)$ from the reward space R that corresponds to the state-action pair (s, a).

The agent's primary objective is to select a policy (or policies) that maps its current state to a probability density function across the possible actions, aiming to maximize the expected future discounted reward $\sum_{k=0}^{\infty} \gamma^k r_t$. The discount factor γ, which lies between 0 and 1, determines the balance between immediate and future rewards.

In this model, the agent's memory capacity is set to 10,000, and a batch size of 64 is used for training. The learning rate for both the actor and critic networks in the DDPG-based EV batteries is set to 0.001. The number of iterations is set to 300, the maximum number of episodes is set to 200, and checkpoints are taken every 100 episodes.

To evaluate the uncertainty in the SoC estimation, a confidence interval of 95percent is utilized. This confidence interval helps measure the reliability and generalizability of the Deep Q-Network (DQN) algorithm in estimating the SoC of EV batteries.

These hyperparameters and settings mentioned provide the specific configuration used in the proposed study for the DQN-based SoC estimation and management of EV batteries in V2G networks.

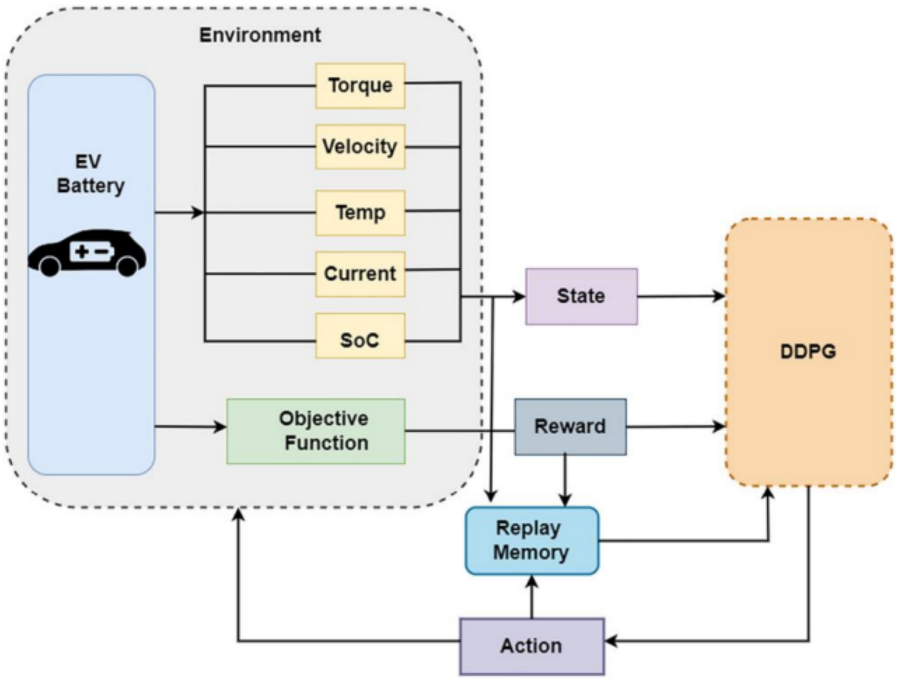

Figure 3.3: Flowchart of the Reinforcement learning method for estimating the SOC of a Li-ion battery.

- STATES: he states (S_t) of the system at any time instance t include various parameters such as State of Charge (SoC) of the battery, velocity, torque, temperature, and current. These parameters provide information about the current state of the EV battery system. $S_t = \{SoC, velocity, torque, temp, current\}$.
- ACTIONS: TThe actions (At) are chosen by the DDPG agent and are continuous in nature. In this system, the action variable is engine power (engine power = f(engine power)). By controlling the engine power, the agent can regulate the amount of energy supplied or consumed by the battery, thus impacting the SoC.
- REWARD: The reward (Rt) at any time instance (t) is used to guide the learning process of the DDPG agent. The reward function aims to maintain the battery SoC within a suitable range throughout the travel period. The reward is calculated based on the deviation of the current SoC (SoCt) from a reference SoC (SoCref). If the SoC stays within the suitable range, the agent receives a positive reward, while exceeding the range results in a negative reward. $R_t = |SoC_{ref} - SoC_t|$.
- OBSERVATIONS: The observations (Ot) are the inputs provided to the agent at each time instance (t) to make decisions about the optimal action to take. These observa-

tions consist of measurements and readings such as SoC, velocity, torque, temperature, current, and other internal battery parameters. $O_t = [k_{1t}, k_{2t}, k_{3t}, \ldots, k_{nt}]$.

3.2 State of Charge Estimation for Lithium Ion Battery Based on LSTM

Recurrent neural networks (RNNs) differ from traditional neural networks by allowing connections between hidden layers to form cycles, enabling them to handle sequential data. This interconnectedness enables RNNs to predict sequences. Additionally, RNNs have a memory mechanism that stores the results of previous computations and applies them to the current output. This means that the nodes between hidden layers are connected, and the inputs of the hidden layer include both the output of the input layer and the previous output of the hidden layer. This memory allows RNNs to capture temporal dependencies and context, making them suitable for tasks involving sequential data, although they can face challenges such as the vanishing or exploding gradient problem, which variants like LSTM and GRU aim to address.

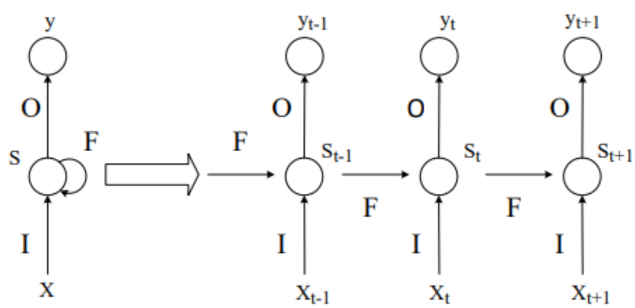

Figure 3.4: Structure of recurrent neural network.

To overcome the issues of gradient explosion or dispersion in traditional RNNs, the long short-term memory (LSTM) network was introduced. LSTM improves the RNN structure by replacing the simple hidden layer with a memory cell, which allows the network to retain and utilize information over longer sequences. The key innovation of LSTM lies in the incorporation of specialized gates, such as the input gate, forget gate, and output gate, which control the flow of information within the memory cell. These gates regulate the memory cell's interactions with the input and output, enabling LSTM to selectively remember or forget information based on the input and the task at hand. By managing the flow of gradients through these gates, LSTM mitigates the problems of gradient explosion or dispersion during backpropagation, allowing for more stable training and improved convergence towards optimal solutions.

The memory cell in a long short-term memory (LSTM) network consists of several components, including the forget gate, input gate, memory cell, and output gate. The forget gate allows the LSTM network to selectively forget or update information stored in the memory

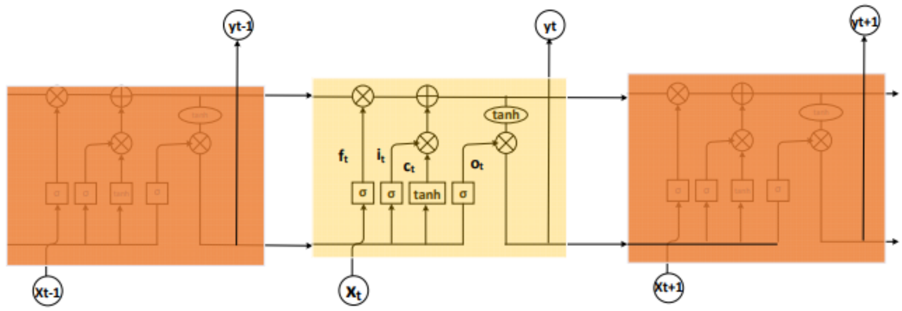

Figure 3.5: Structure of LSTM network.

cell. By incorporating these gates, LSTM can effectively manage and control the flow of information over time, enabling it to capture long-term dependencies and avoid issues caused by individual parameters.

In the context of estimating state of charge (SOC) for batteries, the LSTM network's ability to combine parameters from adjacent time steps is particularly advantageous. This capability helps mitigate the impact of exceptional single parameter values, resulting in more stable SOC estimation. Temperature plays a significant role in battery performance, but it changes slowly over a specific period, and different parts of the battery may have varying temperatures. Therefore, using temperature as an input parameter can introduce significant errors. To address this, the residual capacity of the battery, which reflects the impact of temperature on battery performance, is considered as an input parameter. This allows the LSTM model to capture the temperature-related effects more accurately and improve the accuracy of SOC estimation for batteries.

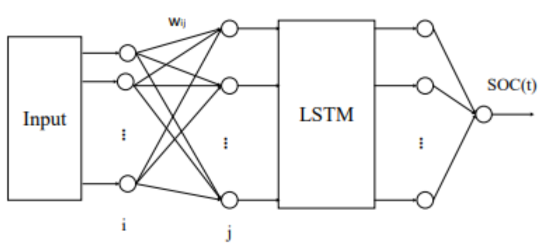

Figure 3.6: Structure of SOC estimation algorithm based on long-short term neural network.

The model described consists of five parts.

- The input layer receives the input data, which could include features or parameters relevant to the problem at hand.
- The fully-connected layer connects the input layer to the LSTM network. This layer is responsible for transforming the input data into a format suitable for the LSTM

network.

- The LSTM network is the core component of the model. It includes the memory cells with their respective forget gates, input gates, memory cells, and output gates. The LSTM network processes the input data sequentially, capturing long-term dependencies and retaining memory across time steps.
- The fully-connected layer connects the LSTM network to the output layer. This layer transforms the output of the LSTM network into a format suitable for the final output.
- The output layer produces the final output of the model, which could be predictions, classifications, or any other desired outcome based on the problem being solved.

Overall, this model architecture combines the input layer, fully-connected layers, and LSTM network to capture temporal dependencies and produce accurate predictions or classifications through the output layer.

SOC estimation Algorithm

$$
\begin{aligned}
x &= iwb \\
f_t &= \sigma(W_h x + b_f) \\
i_t &= \sigma(W_h x + b_i) \\
\tilde{C}_t &= \tanh(W_h x + b_c) \\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\
o_t &= \sigma(W_h x + b_o) \\
h_t &= o_t \cdot \tanh(C_t) \\
y &= h_t W_b
\end{aligned}
$$

Where $\mathbf{x}t$ is the input vector; w_t and b_t are the values of the weight and bias between the input layer and the LSTM network at time t, respectively. $ht-1$ is the output value of the LSTM network at the previous time; w_f, w_i, w_j, and w_o are the weight values of the forget gate, the input gate, the memory unit, and the output gate, respectively; b_f, b_i, b_c, and b_o are the biases of the forget gate, the input gate, the memory unit, and the output gate, respectively; f_t, ϕ_t, C_t, and o_t are the output values of the forget gate, the input gate, the memory unit, and the output gate, respectively; C_t is the state of the LSTM network at the current time; h_t is the output value of the LSTM network at the current time; w_k and b_k are the values of the weight and bias between the LSTM network and the output layer; Finally, y_t is the value of the estimated SOC at time t.

3.3 State of Charge Estimation for Lithium Ion Battery Based on CNN

3.3.1 Network Model for SOC Estimation

To exploit the temporal information and the interrelations in the multiple measurable variables of the battery for SOC estimation, stack their values obtained at n time instants as a matrix:

$$\mathbf{X}_t = [\mathbf{x}_t, \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-n+1}], \quad \text{with} \quad \mathbf{x}_t = [V_t, I_t, T_t]^T \tag{3.2}$$

the data of the different measurable variables are normalized using

$$x_{\text{normalized}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3.3}$$

where x_t is the value of a specific measurable variable acquired at time t, and $x_{\max}$ and $x_{\min}$ are its possible maximum and minimum values, respectively.

3.3.2 CNNs and Residual Blocks

Convolution Layer: A convolution layer performs a dot product (convolution operation) between a kernel (or filter) and a portion of the input data. This operation is applied across the entire input space to produce a feature map. Multiple filters can be used to extract different aspects of input-data characteristics.

Pooling Layer: The pooling layer is responsible for downsampling the feature maps obtained from the convolutional layers. It extracts non-overlapping patches (e.g., 2x2) from the feature map and computes the average or maximum of the features within each patch. This downsampling reduces sensitivity to positional changes of features in the original maps.

Fully Connected Layer: Neurons in a fully connected layer have connections to all activations in the previous layer. In this layer, the results from the convolutional and pooling layers are considered to make classification decisions or regression predictions. Before connecting to a fully connected layer, the feature map is typically flattened into a one-dimensional array of numbers or vectors.

Activation Function: The output layer of the network applies an activation function, which depends on the task being performed. For classification tasks, the softmax function is commonly used to produce probabilities for different classes. For regression tasks, the identity function (f(x) = x) is often adopted to directly output the regression value.

3.3.3 Architecture

Residual Blocks: The input-data matrix is first fed into two residual blocks. Each residual block consists of a convolution layer, an average pooling layer, and a shortcut connection. The convolution layer in each block uses 16 filters of size 3x3.

Shortcut Connection: The shortcut connection adds the input of a residual blockto its output feature maps. This connection helps preserve important information from the input during the pooling operation. In this case, the shortcut connection incorporates a 1x2 average pooling filter.

Average Pooling Layers: The average pooling layers downsample the feature maps using 1x2 filters, reducing the spatial dimensions.

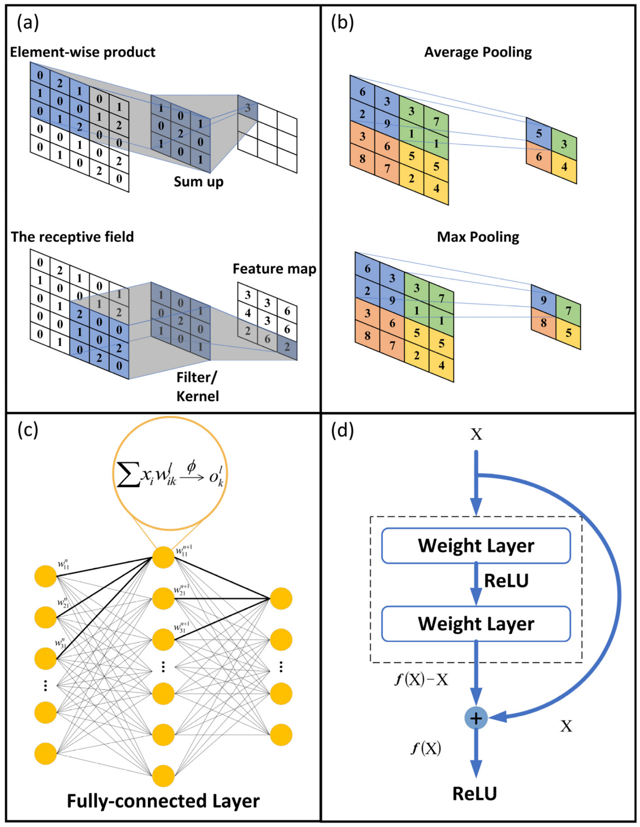

Figure 3.7: Composition blocks of a residual convolutional neural network. (a) A convolution layer and a convolution operation (b) A pooling layer and two typical pooling operations (c) A series of three fully connected layers having different numbers of neurons. (d) A conceptual residual block.

Fully Connected Layers: To regress the results from the residual blocks for SOC estimation, three fully connected layers are added in series. The sizes (number of neurons) of these layers are 32, 16, and 8, respectively. These layers are connected without any intervening layer.

Shortcut Connection for SOC Estimation: Inspired by the Kalman-filter-based approach, a shortcut connection is introduced to directly include the current measurement vector of the battery. The global average pooling operation flattens the feature maps by taking the average of each feature map and stacking them as a data vector.

Activation Functions: All trainable layers in the network, except the output layer, employ the ReLU activation function. The output layer uses the identity activation function.

Loss Function: The Mean Absolute Error (MAE) given in Equation (3) is used as the loss function to measure the difference between the predicted SOC values and the ground truth.

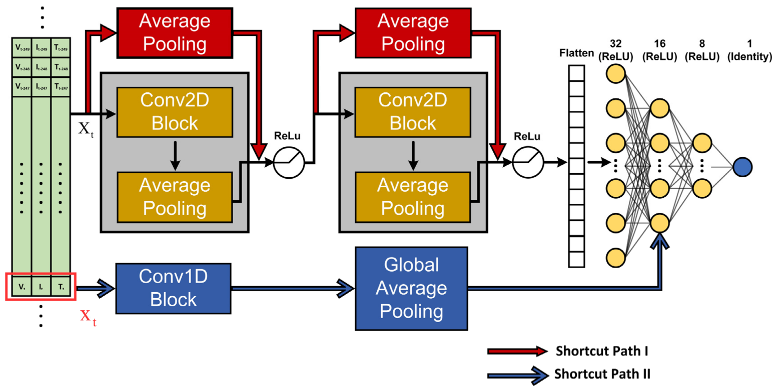

Figure 3.8: Neural Network Model for SOC Estimation.

Optimization: The network parameters are optimized using the Adam optimizer. Adam is a stochastic optimization method that combines the advantages of adaptive gradients and RMSProp. It uses a randomly selected subset of data to create a stochastic approximation of the gradient. The algorithm calculates exponential moving averages of the gradients and squared gradients, with parameters and controlling the decay rates of these moving averages. These parameters are important hyperparameters to set in the Adam optimizer.

Data Inclusion: The previous data vectors are included in SOC estimation because past voltages, currents, and temperatures can impact the current SOC due to the capacitive effect in the battery. Discarding this previous data could result in a loss of valuable information. However, including a large volume of data poses challenges in extracting discriminant information for the task. Therefore, a scheme to prevent the model from being overwhelmed by a massive amount of data needs to be considered.

Filters and Pooling: Filters in the convolution layers are applied across the entire input space, similar to the multivariate autoregressive (MVAR) model. The MVAR model, formed by a weighted linear sum of input-data vectors, can predict future data vectors. The learnable parameters in the filter correspond to the predictor coefficients in the MVAR model. Different filters can lead to different MVAR models. The pooling operation, specifically average pooling with a size of 1x2, is applied in the row direction (time indices) of the input-data matrix . This allows noisy activations to be discarded, and no learnable parameters are present in the pooling layers.

Chapter 4

Experiments And Results

4.1 Experimental Setup

4.1.1 BMW dataset

- The BMW dataset consists of a collection of time-series data recorded from lithium-ion batteries. It includes measurements of battery voltage, current, temperature, and SOC. The dataset comprises a large number of samples, capturing various operating conditions and discharge profiles.High-voltage batteries in battery electric vehicles face significant load fluctuations due to driving behavior. This dynamic performance of the powertrain is contrasted by the almost constant load of the auxiliary consumers. The highest auxiliary consumption is generated by the heating and air conditioning system, which decreases the vehicles range significantly. 72 real driving trips with a BMW i3 (60 Ah) were recorded, serving for model validation of a full vehicle model consisting of the powertrain and the heating circuit.
  Each trip contains:
  - Environmental data (temperature, elevation, etc.)
  - Vehicle data (speed, throttle, etc.)
  - Battery data (voltage, current, temperature, SoC)
  - Heating circuit data (indoor temperature, heating power, etc.)

  The measurement data is in CSV format to ensure easy use by various standard programs (Excel, Matlab) or own developed codes (Python).
  The script "readin.m" reads the csv files into MatLab as table and struct.
  The data contains vehicle data, battery data and heating data.
  The measurement data is divided into two categories. Category A was recorded in summer and does not contain all measured data due to trouble with the measurement system. Category B was recorded in winter and is consistent.
  Data Collection Methodology: The BMW dataset was obtained through controlled experiments where lithium-ion batteries were subjected to different discharge scenarios. The battery parameters and measurements were recorded using specialized equipment and sensors.

Time [s]	Battery Current [A]	Battery Voltage [V]	Battery Temperature [°C]	SoC [%]
0	-15.80	371.80	-1.0	65.0
0.1	-15.89	371.78	-1.0	65.0
0.2	-16.19	371.73	-1.0	65.0
0.3	-16.27	371.70	-1.0	65.0
0.4	-15.87	371.70	-1.0	65.0
...	...	...	...	...
1642.4	-4.00	367.15	3.0	48.8
1642.5	-4.20	367.20	3.0	48.8
1642.6	-4.05	367.15	3.0	48.8
1642.7	-3.90	367.10	3.0	48.8
1642.8	-3.90	367.10	3.0	48.8

[16429 rows x 5 columns]

- Preprocessing Steps:
  - Data Normalization: The dataset underwent normalization to ensure all input features were scaled consistently. Common normalization techniques, such as min-max scaling or z-score normalization, were applied to bring the features within a similar range.
  - Feature Extraction: Relevant features, such as voltage and current profiles, were extracted from the raw dataset. Additional features, such as temperature, may also have been considered depending on the specific research goals.
  - Splitting into Training and Testing Sets: The dataset was divided into training and testing subsets to evaluate the performance of the models accurately. A common approach is to use a certain percentage (e.g., 80%) of the data for training and the remaining portion for testing.

- Hardware and Software Environment:
  - Computational Resources: The experiments were conducted on a specific hardware setup, including the CPU, GPU, and memory specifications. The computational resources were chosen based on their capacity to handle the complexity of the deep learning models and the size of the dataset.

– Deep Learning Frameworks: Popular deep learning frameworks, such as TensorFlow, PyTorch, or Keras, were employed to implement and train the reinforcement learning, CNN, and LSTM models. These frameworks provide efficient tools and libraries for building and optimizing deep learning architectures. High-voltage batteries in battery electric vehicles face significant load fluctuations due to driving behavior. This dynamic performance of the powertrain is contrasted by the almost constant load of the auxiliary consumers. The highest auxiliary consumption is generated by the heating and air conditioning system, which decreases the vehicles range significantly. 72 real driving trips with a BMW i3 (60 Ah) were recorded, serving for model validation of a full vehicle model consisting of the powertrain and the heating circuit.

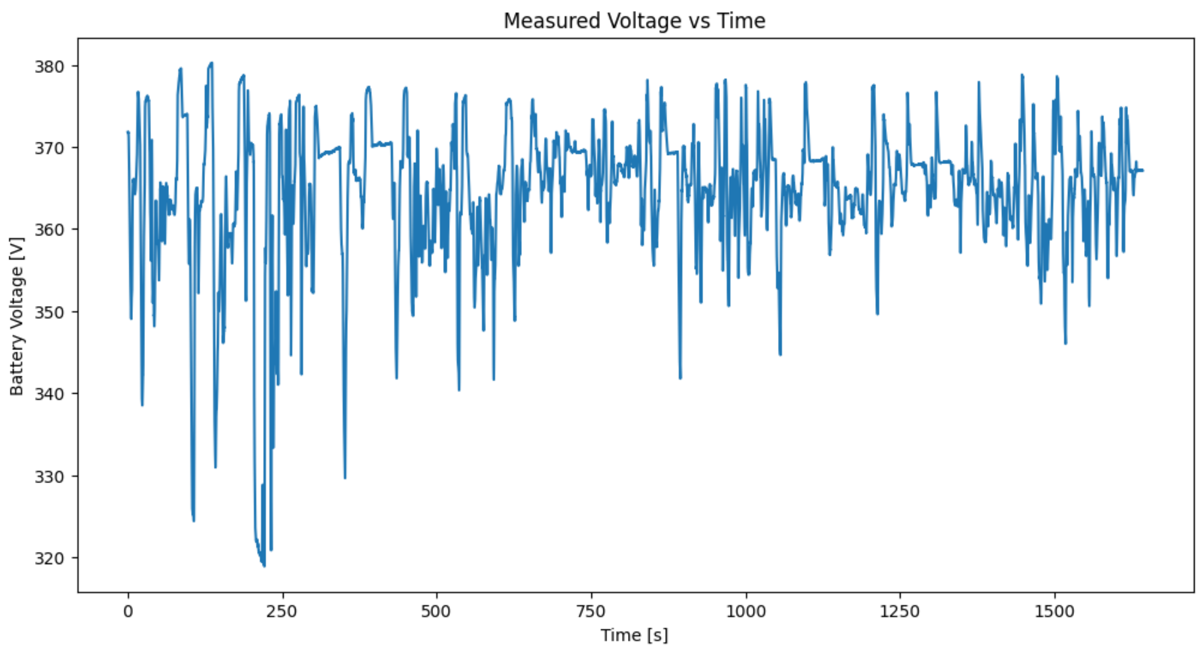

Figure 4.1: visualize the battery voltage over time using the data

4.2 Implemetation by Reinforcement Learning

Neural Network Architecture:

- The DQN class defines the neural network model used in the Deep Q-Learning agent.
- The architecture consists of three fully connected layers: fc1, fc2, and fc3.
- The ReLU activation function (relu) is applied between the layers to introduce non-linearity.

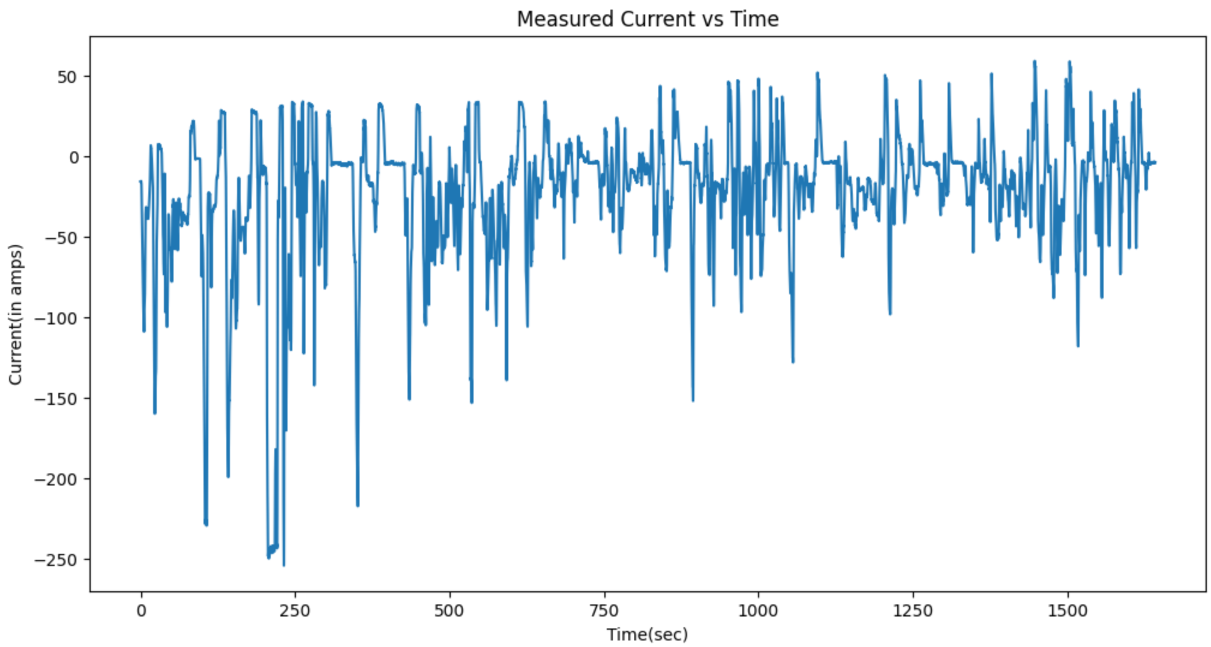

Figure 4.2: visualize the battery current over time

Deep Q-Learning Agent:

- The DQNAgent class encapsulates the reinforcement learning agent for state of charge (SoC) estimation.
- The agent is initialized with the state and action dimensions, learning rate, discount factor (gamma), and exploration rate (epsilon).
- The model attribute represents the DQN neural network.
- The optimizer is defined using the Adam optimizer with the specified learning rate.
- The mean squared error (MSELoss) criterion is used to compute the loss.

Action Selection:

- The select action method is responsible for choosing an action based on the current state.
- With probability epsilon, a random action is chosen to encourage exploration.
- Otherwise, the model is used to estimate the Q-values for each action, and the action with the highest Q-value is selected.

Training:

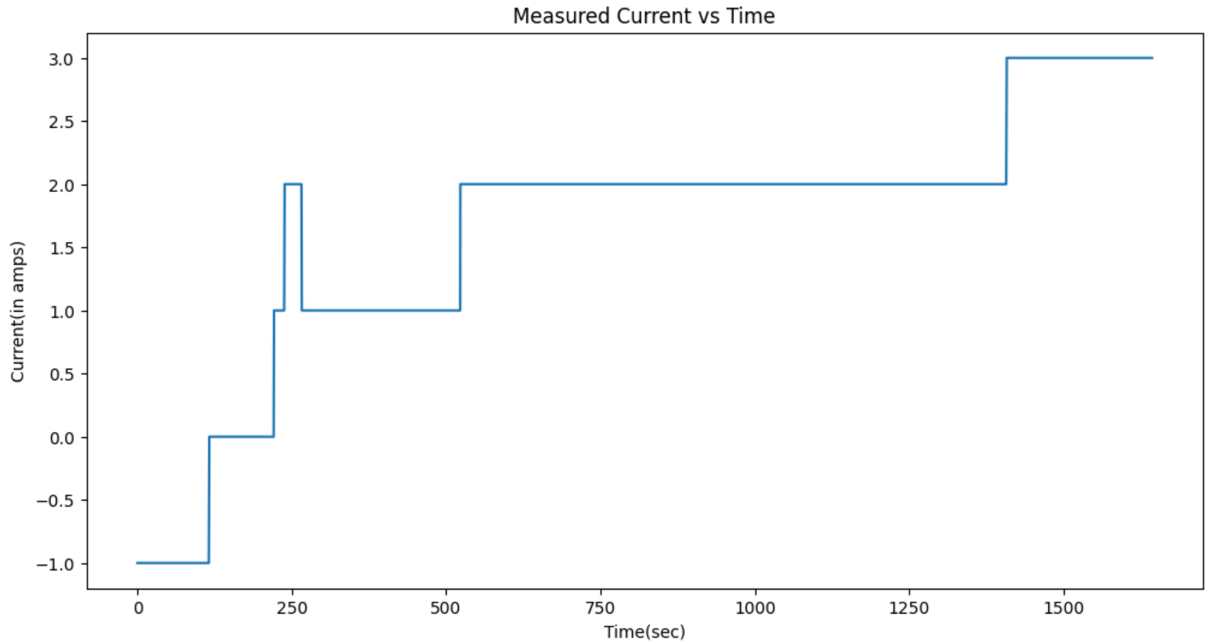

Figure 4.3: Measured Current vs Time

- The train method updates the DQN model using the Q-learning algorithm.
- It takes the current state, selected action, next state, reward, and termination flag (done) as inputs.
- The Q-values for the current state are computed, and the target Q-value is updated using the next state's maximum Q-value.
- The optimizer is then used to minimize the mean squared error between the predicted and target Q-values.

Training Loop:

- The train agent method is responsible for training the DQNAgent over a specified number of episodes.
- It initializes the state, sets the total reward to zero, and begins the training loop.
- The action is selected based on the current state, and the next state and reward are obtained by performing the action.
- The train method is called to update the model based on the observed state, action, next state, reward, and termination flag.
- The state is updated, and the total reward is accumulated.

- The progress of training is printed by displaying the episode number and the total reward.

Results and Evaluation:

- The results of training the DQNAgent can be evaluated based on the convergence of the total reward over episodes.
- Higher total rewards indicate better SoC estimation performance.
- The training progress can be visualized by plotting the total reward over episodes or by analyzing other metrics such as the mean reward or accuracy.
- Implements a Deep Q-Learning agent using a Deep Q-Network (DQN) to predict the state of charge (SoC) of a battery based on temperature, voltage, current, and time data.
- The agent is trained using the Q-learning algorithm and then tested to generate predicted SoC values.

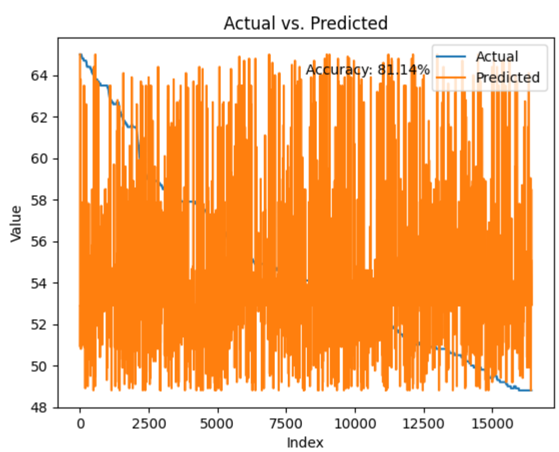

Figure 4.4: SOC Estimation Graph by RL

Hyperparameter Configuration

- Dimensionality of the state space. In this case, the state space consists of four variables: temperature, voltage, current, and time. Each variable represents a feature that is used to estimate the SoC of the battery.
- The number of possible actions in the reinforcement learning agent is represented by action dimension. The temperature variable is used to compute the number of data points in the dataset, and subtracting 1 accounts for the fact that the last data point does not have a corresponding action.

- Learning rate, which determines the step size at which the reinforcement learning agent updates its internal model based on the observed rewards.
- Gamma determines the weight given to future rewards compared to immediate rewards. A higher discount factor places more emphasis on future rewards.
- exploration rate, which determines the probability of the agent taking a random action instead of the one predicted by its current policy. A higher exploration rate encourages more exploration of the action space.

Testing the agent

During testing, the agent predicts the SoC values based on the given input features, which include temperature, voltage, current, and time.After the iterations, the code prints the predicted SoC values stored in predicted soc, along with the length of the list.

SoC [%]
65.0
65.0
65.0
65.0
65.0
...
48.8
48.8
48.8
48.8
48.8

[16429 rows x 1 columns]

Accuracy

$$\text{Accuracy} = \frac{\sum_{(a,p)\in \text{zip}(values\_list, predicted\_soc)} 1 \text{ if } |a-p| < 6}{\text{len}(values\_list)} \times 100$$

4.3 Implemetation by LSTM

Input Preparation:

The input features are extracted including time, battery current, battery voltage, and battery temperature.

Data Split:

The data is split into training and test sets.The test set size is set to 25% of the total data.

Input Data Reshaping:

The training and test input data are reshaped to match the expected input shape of the LSTM model.Reshaping is done to add an additional dimension, reflecting the (*batch_size, time_steps, input_dim*) format expected by the LSTM model.

Model Definition:

An LSTM layer with 128 units is added as the first layer A dense layer with 1 unit is added as the output layer, predicting the SoC percentage.

The model is compiled using the mean squared error (MSE) loss function and the Adam optimizer.

Model Training:

The model is trained using the training data (**X_train** and **y_train**). During training, the model adjusts its parameters to minimize the mean squared error (MSE) loss and improve the prediction accuracy.

Model Evaluation:

The trained model is evaluated on the test set using the evaluate function, calculating the loss value (MSE) for the test data.

SoC Prediction:

The model predicts the SoC percentage for the test set using the predict function.

Result Visualization:

A plot is created to compare the actual SoC values with the predicted SoC values . The plot helps visualize the performance of the model and how well it predicts the SoC. This approach of using LSTM neural networks is effective for modeling sequences, such as time series data, and can provide valuable insights into predicting the SoC of batteries.

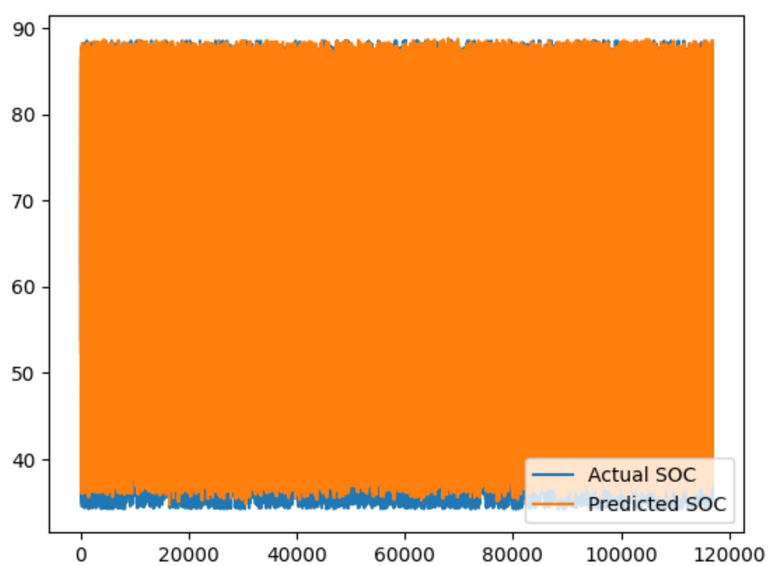

Figure 4.5: SOC Estimation Graph by LSTM

4.4 Implemetation by CNN

Training and Testing Sets

- 20% of the data will be used for testing, while the remaining 80% will be used for training.
- random seed value to 42, ensuring that the data split is reproducible. Using the same seed value will yield the same split every time the code is run.
- The `train_test_split` function returns four sets of data: `X_train`, `X_test`, `y_train`, and `y_test`.

Neural Network Model for State of Charge (SoC) Prediction
The model architecture consists of three fully connected layers

- self.fc1 creates the first fully connected layer with `input_size` number of input features and 16 output features.
- self.fc2 creates the second fully connected layer with 16 input features and 8 output features.
- self.fc3 creates the final fully connected layer with 8 input features and 1 output feature.

Loss function

An instance of the mean squared error (MSE) loss function from the `nn.MSELoss` class. This loss function is commonly used for regression tasks, such as predicting a continuous value like the State of Charge (SoC). The MSE loss measures the average squared difference between the predicted and target values.

Neural Network Training Loop

- The number of training epochs to 100, indicating the number of times the entire training dataset will be passed through the model.
- The batch size to 32, specifying the number of samples processed in each iteration of the training loop.

Test Loss

The loss between the predicted outputs and the test target values is calculated to measures the discrepancy between the predicted values and the actual target values.

Finally, the test loss is providing a quantitative measure of the model's performance on the test dataset. A lower test loss indicates a better ability of the model to generalize and make accurate predictions on unseen data.

Evaluating the model on the test dataset is crucial for assessing its performance in real-world scenarios. It helps to validate the model's ability to generalize to unseen examples and provides insights into its predictive capabilities beyond the training data.

Mean Absolute Error (MAE)

Calculates the MAE by comparing the test targets (actual values) with the predicted labels.Subtracting the MAE from 1 provides an accuracy score.

Chapter 5

Conclusion

The project focused on the state-of-charge (SOC) estimation of lithium-ion batteries using reinforcement learning, convolutional neural networks (CNNs), and long short-term memory (LSTM) networks, utilizing the BMW dataset for evaluation. The objectives of the project were to improve the accuracy, adaptability, and robustness of SOC estimation by leveraging the power of reinforcement learning techniques and the capabilities of CNNs and LSTM networks.

Through the application of reinforcement learning, a reinforcement learning agent was trained to interact with the battery system and learn optimal policies for SOC estimation. The agent underwent trial and error interactions, receiving feedback on its actions, and adjusting its strategies to maximize the SOC estimation performance. This allowed the agent to learn from the data and improve its estimation accuracy over time.

The CNNs were utilized to extract spatial features from the battery voltage data. By processing the voltage data through multiple convolutional layers, the CNNs were able to capture important spatial patterns and relationships, enhancing the SOC estimation accuracy. The CNNs effectively learned to identify relevant features in the voltage data, enabling more precise estimation of the SOC.

Additionally, the LSTM networks were employed to capture the temporal dependencies present in the battery voltage data. LSTM networks are well-suited for sequential data analysis, and their ability to model long-term dependencies makes them suitable for SOC estimation tasks. By considering the historical voltage data and capturing the dynamics of the battery system, the LSTM networks improved the adaptability and robustness of the SOC estimation.

The evaluation of the proposed approach was conducted using the BMW dataset, which provided real-world battery data for comprehensive analysis. The experimental results demonstrated the effectiveness of the reinforcement learning-based CNN and LSTM models in accurately estimating the SOC of lithium-ion batteries. The combined approach yielded significant improvements in SOC estimation accuracy compared to traditional methods.

The project's findings have practical implications for battery management systems, as accurate SOC estimation is crucial for optimizing battery usage, enhancing performance, and prolonging battery lifespan. The proposed approach provides valuable insights into leveraging reinforcement learning, CNNs, and LSTM networks for SOC estimation, contributing to the advancement of battery management techniques.

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