Uncertainty-Aware State of Charge Estimation for Lithium-Ion Batteries with Gated Recurrent Unit and Deep Evidential Regression

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Abstract: High-energy-density batteries are gaining popularity with the rise of electric vehicles (EVs). State-of-charge (SOC) estimation is crucial for informed decision-making, operational safety, and the longevity of these batteries; however, model-based SOC estimation often struggles due to the nonlinear dynamics of batteries, unpredictable measurement noise, and dynamic loading conditions. Model-free data-driven methods provide an alternative solution. However, they often struggle to process a long sequence of temporal dependencies in the input data. Furthermore, uncertainty awareness associated with the estimated SOC is often unavailable. This work presents an uncertainty-aware SOC estimation framework integrating a Gated Recurrent Unit (GRU) network with deep evidential regression. Our framework processes sequential time-series data to estimate SOC and its associated uncertainty in a single forward pass. Validation results on real-world battery cycling datasets show that, for in-distribution data, our method achieves predictive performance comparable to computationally intensive ensemble methods.

Keywords: Energy Management Systems, State Estimation, Deep Learning, Uncertainty Quantification

1. INTRODUCTION

With the growing emphasis on renewable energy generation, smart grid integration, and large-scale electric vehicle (EV) production, energy storage systems (ESS) are gaining increasing attention. Lithium-ion batteries (LIBs) have emerged as the preferred choice among various storage technologies due to their high energy density, superior power capacity, and efficient storage characteristics. However, LIBs present several challenges, including fire and explosion hazards (Zalosh et al., 2021), high manufacturing costs, and complex nonlinear electrochemical dynamics. Recent research efforts have focused on enhancing storage efficiency, improving operational safety, and extending battery lifespan through real-time monitoring of key dynamic parameters, particularly the state of charge (SOC). The SOC represents the remaining discharge capacity of a battery relative to its rated capacity, making it a critical parameter for optimizing performance and ensuring safe operation. However, SOC cannot be directly measured and must be estimated using various approaches, including circuit-based models, model-based estimation techniques, and data-driven methods. Although easy to implement, circuit-based methods are limited in their application to real-time scenarios due to their long observation times. Model-based methods depend heavily on parameter estimation, which depends on temperature, battery aging and loading conditions. Data-driven methods, specifically *Deep Neural Networks (DNNs)*, are a viable alternative that process observable sensor data to estimate SOC. Different combinations of DNNs are explored to achieve significant accuracy in SOC estimation. However, awareness of uncertainty in SOC estimation remains underexplored in the current literature, despite its importance for decision-making. Estimating the breakdown of total uncertainty into aleatoric and epistemic components is just as crucial as estimating the total uncertainty itself. For example, high total uncertainty can justify conservative range estimation for EVs; high aleatoric uncertainty suggests applying probabilistic models to improve robustness, while high epistemic uncertainty indicates the need to collect more data and refine the model.

In this work, we present a state-of-charge (SOC) estimation framework that utilizes a GRU-based recurrent neural network to process sequential sensor data, including current, voltage, and temperature, for estimating the SOC of lithium-ion batteries. To quantify the uncertainty associated with each SOC prediction, we integrate deep evidential regression, capturing both aleatoric and epistemic components. In parallel, we apply a model ensemble method to establish a baseline uncertainty estimate and assess the calibration of the evidential regression. To the best of our knowledge, this is the first work to combine deep evidential regression with GRU for SOC estimation, incorporating uncertainty information.

Our key contributions are as follows:

- We propose a hybrid SOC estimation pipeline [1] combining GRU-based temporal modeling with deep evidential regression for uncertainty-aware prediction.
- We incorporate a model ensemble method to calibrate deep evidential regression method for increased accuracy of uncertainty estimation.

2. BACKGROUND

The current literature approaches the SOC estimation problem from three different angles.

Circuit principle methods, such as the Coulomb counting method (Ng et al., 2009) and open-circuit voltage (OCV) methods (Xing et al., 2014), are easy to implement but struggle with real-time applications. Coulomb counting methods are prone to errors (i.e, current measurement, current integration, battery capacity etc) (Movassagh et al., 2021). In the OCV method, the terminals do not reflect the actual OCV due to the voltage relaxation process, which is further slowed down at lower temperatures. Additionally, LIBs exhibit hysteresis during charging and discharging, which makes SOC estimation from OCV more uncertain (Zheng et al., 2018).

Model-based estimation methods utilise online measurements of current and voltage as model inputs. The most common lithium-ion battery (LIB) models include electrochemical, equivalent circuit, and internal impedance models. However, their practical application is limited by several challenges. Electrochemical models involve high computational complexity, requiring a thorough understanding of the system (Li et al., 2017), making real-time implementation difficult. These models often incorporate adaptive filtering techniques such as Kalman filters, Unscented Kalman Filters (UKF), and Particle Filters (PF) to improve estimation accuracy (How et al., 2019).

Data-driven methods, specifically deep learning approaches, have emerged as viable alternatives to model-based SOC estimation (Tian et al., 2023). Various *Deep Neural Networks (DNNs)* have been applied for this task. Traditional *Fully Connected Neural Networks (FCNNs)* demonstrated high accuracy in SOC estimation (Chemali et al., 2018) but suffer from an explosion in the number of parameters when processing long sequences. *Recurrent Neural Networks (RNNs)* inherently handle sequential data better and have demonstrated superior performance compared to FCNNs. However, they face gradient vanishing and exploding issues for long input sequences (Bengio et al., 1994).

To overcome these limitations, Gated RNNs, such as *Long Short-Term Memory (LSTM)* and *Gated Recurrent Units (GRU)*, introduce gating mechanisms to regulate information flow and capture long-term dependencies. LSTMs have shown exceptional performance in various domains, including time series forecasting (Siami-Namini et al., 2019), machine translation (Sutskever et al., 2014), and healthcare diagnostics (Balaji et al., 2021). However, their complex architecture and high computational cost hinder real-time deployment. To balance computational efficiency and accuracy, *GRUs* were developed, offering comparable performance with a simpler structure Yang et al. (2019), making them more suitable for real-time applications such as state estimation and control of dynamic systems (Rasul and Yoon, 2025). However, these models are still slow to train and do not leverage the parallel GPU computation. Due to these limitations, recurrent models are generally superseded by another architecture known as Transformer in many domains such as computer vision (Bazi et al., 2021). Hannan et al. (2021) explored a transformer-based soc estimation method with fewer training data and achieved significant accuracy. Despite their success, these methods often lack awareness of the uncertainty associated with SOC estimation.

Uncertainty estimation primarily focuses on either epistemic uncertainty (Model Uncertainty) or aleatoric uncertainty in deep learning. Bayesian approximation and ensemble techniques are two widely used methods for estimating uncertainty (Abdar et al., 2021). Bayesian approximation is practically achieved by the Monte Carlo (MC) dropout method, where specific neurons are kept shut during the inference process to estimate the epistemic uncertainty in deep learning (Gal and Ghahramani, 2016). Lakshminarayanan et al. (2017) presented an ensemble method that estimates aleatoric uncertainty by measuring variance during training different DNNs with different initialization. This method can also estimate epistemic uncertainty by analyzing the disagreement among the models. However, both ensemble and MC dropout methods require multiple forward passes of the test data through the model, which is computationally expensive. Amini et al. (2020) suggested a deep evidential regression method that estimates evidential distribution parameters in a single forward pass. This approach significantly reduces computational cost and is more suitable for real-world applications. Nonetheless, its practical adoption has been limited due to the need for extensive fine-tuning of the regularization term.

3. PROPOSED FRAMEWORK

3.1 Dataset

We use the CALCE Battery dataset (CALCE, 2024) for SOC estimation. The dataset provides detailed cycling data, including voltage, current, temperature, charge capacity and discharge capacity under different loading conditions such as *DST(Dynamic Stress Test)*, *US06 (US06 Highway Driving Schedule)* and *FUDS(Federal Urban Driving Schedule)* both of which are designed to simulate discharge mode of EV battery by US Advanced Battery Consortium (USABC). Finally, the framework is also evaluated with the *BJDST (Beijing Dynamic Stress Test)* dataset. A time series plot of the DST dataset is illustrated in Figure 1.

3.2 GRU Structure

The proposed GRU structure consists of different *Neural Network (NN)* layers. The input layer processes different battery measurements like current, voltage, temperature, etc, sampled at regular intervals. The input sequence is structured using a sliding window of length T, capturing the temporal dependencies in battery dynamics. GRU layer allows the network to selectively retain relevant

[1] `https://github.com/arasul42/soc_gru_evidential`

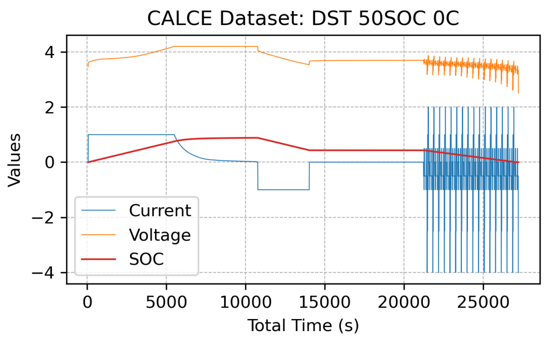


Fig. 1. CALCE dataset (25°C with DST at 50% SOC)

historical information while discarding redundant signals, leading to efficient learning of SOC evolution patterns.

As shown by Chung et al. (2014), we can compute hidden state h_t at each time step t, as a convex combination of the previous hidden state h_{t-1} and the candidate hidden state $\tilde{h}_t$, regulated by the update gate z_t:

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{1}$$

The update and reset gates are computed as:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{2}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{3}$$

The candidate hidden state $\tilde{h}_t$ is derived using the reset gate:

$$\tilde{h}_t = \tanh(W_h \cdot [r_t \cdot h_{t-1}, x_t]) \tag{4}$$

Here, $\sigma(\cdot)$ represents the sigmoid activation function, $\tanh(\cdot)$ is the hyperbolic tangent. The weight matrices W_z, W_r, and W_h are learnable weight parameters that are optimized during training. The gating mechanism is shown in Figure 2.

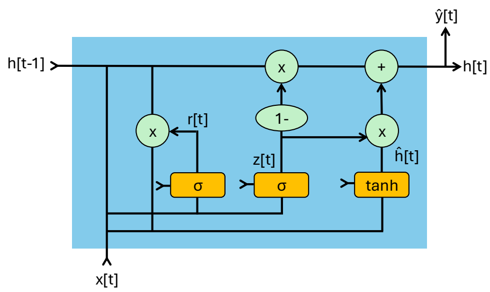


Fig. 2. Gating mechanism of GRU

The final hidden states of the GRU layer are passed through a fully connected layer, which generates the desired outputs. For the fully connected layer structure and activation functions, we followed the LSTM implementation structure by Wong et al. (2021), who applied LSTM models for SOC estimation on the LG 18650HG2 Dataset (Kollmeyer et al., 2020).

3.3 *Uncertainty Estimation*

We deploy the evidential regression method for uncertainty estimation (Amini et al., 2020). The model directly predicts the parameters of a Normal-Inverse Gamma (NIG) distribution. Given an input sequence x, the network outputs four values: the predictive mean γ, and three parameters ν, α, and β as illustrated in Figure 3. The SOC and associated uncertainties can be estimated from the NIG distribution parameters:

$$\hat{\mu} = \mathbb{E}[\mu] = \gamma \tag{5}$$

$$\sigma^2_{\text{aleatoric}} = \frac{\beta}{\alpha - 1} \tag{6}$$

$$\sigma^2_{\text{epistemic}} = \frac{\beta}{\nu(\alpha - 1)} \tag{7}$$

We train the network using a loss function that combines the negative log-likelihood (NLL) of the target under a Student-t marginal distribution with a regularization term that penalizes incorrect predictions made with high confidence. The total loss is expressed as:

$$\mathcal{L} = \mathcal{L}_{\text{NLL}} + \lambda \mathcal{L}_{\text{reg}} \tag{8}$$

Where λ is a regularization coefficient, and the two components are defined as:

$$\begin{aligned} \mathcal{L}_{\text{NLL}} = &\frac{1}{2}\log\left(\frac{\pi}{\nu}\right) - \alpha\log(\Omega) \\ &+ \left(\alpha + \frac{1}{2}\right)\log\left((y-\gamma)^2\nu + \Omega\right) \\ &+ \log\left(\frac{\Gamma(\alpha)}{\Gamma(\alpha + \frac{1}{2})}\right) \end{aligned} \tag{9}$$

$$\mathcal{L}_{\text{reg}} = |y - \gamma| \cdot (2\nu + \alpha) \tag{10}$$

Here, $\Omega = 2\beta(1+\nu)$. This approach enables a single model to efficiently estimate both aleatoric and epistemic uncertainty, without the computational overhead associated with deep ensembles or sampling-based methods. However, the effectiveness of this method depends significantly on the careful tuning of the hyperparameter λ. Assigning a high value to λ can lead to inflated uncertainty estimates, while a low value may result in overconfident predictions. To determine the optimal value of λ, hyperparameter tuning strategies such as random search (Bergstra and Bengio, 2012) or Bayesian optimization (Rasul et al., 2025) can be employed. In this study, we utilize a model ensemble as a baseline to calibrate and fine-tune λ for improved uncertainty estimation.

Given an ensemble of M models, each model m produces a prediction $\hat{\mu}_m$ for a given input x. The ensemble mean prediction & epistemic uncertainty is given by:

$$\bar{\mu} = \frac{1}{M}\sum_{m=1}^{M}\hat{\mu}_m \tag{11}$$

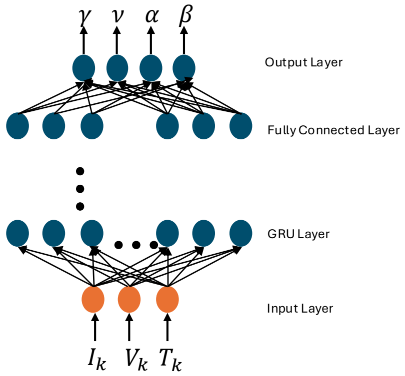


Fig. 3. Evidential regression learning

$$\sigma^2_{\text{epistemic}}(x) = \frac{1}{M}\sum_{m=1}^{M}(\hat{\mu}_m - \bar{\mu})^2 \tag{12}$$

3.4 Evaluation Method

To evaluate the accuracy of the SOC estimation, we use *Root Mean Squared Error (RMSE)* and *Mean Absolute Error (MAE)* as the primary performance metrics. RMSE quantifies the average squared difference between the estimated and true SOC values, emphasizing larger errors. In contrast, MAE measures the average magnitude of the absolute error, providing a more balanced view of overall prediction accuracy.

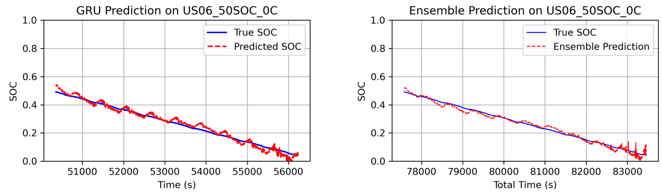
$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{s}_t - s_t)^2} \tag{13}$$

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|\hat{s}_t - s_t| \tag{14}$$

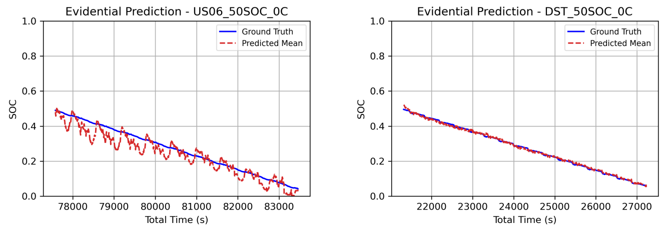
Here, $\hat{s}_t$ is the estimated state-of-charge at time t, s_t is the corresponding ground truth SOC, and T is the total number of time steps over which the evaluation is conducted.

4. EXPERIMENT & RESULT:

We generate input sequences consisting of 100 time steps for model training. The training data is sourced exclusively from the dynamic discharge portion of the CALCE battery dataset, specifically utilizing the Dynamic Stress Test (DST) profile at different initial SOC and operating temperature combinations. Three GRU-based models are trained and evaluated: a single GRU model, an ensemble of five GRU models, and a GRU model incorporating evidential regression for uncertainty estimation. To assess generalization performance, the models are tested on several unseen dynamic drive cycle datasets, including FUDS, US06, and BJ-DST. Experimental results show that the ensemble model achieves the most consistent performance with the best RMSE in 3 out of 5 test datasets, followed by the single GRU model and the evidential regression model. Experiment results are summarized in Table 1 and representative plots are shown in Figure 4. As expected, we found that the evidential regression model performs better with in-distribution(ID) data (DST Profile) compared to out-of-distribution (OOD) data, as shown in Figure 4d.



(a) Single model (b) Model ensemble



(c) Evidential regression (OOD) (d) Evidential regression (ID)

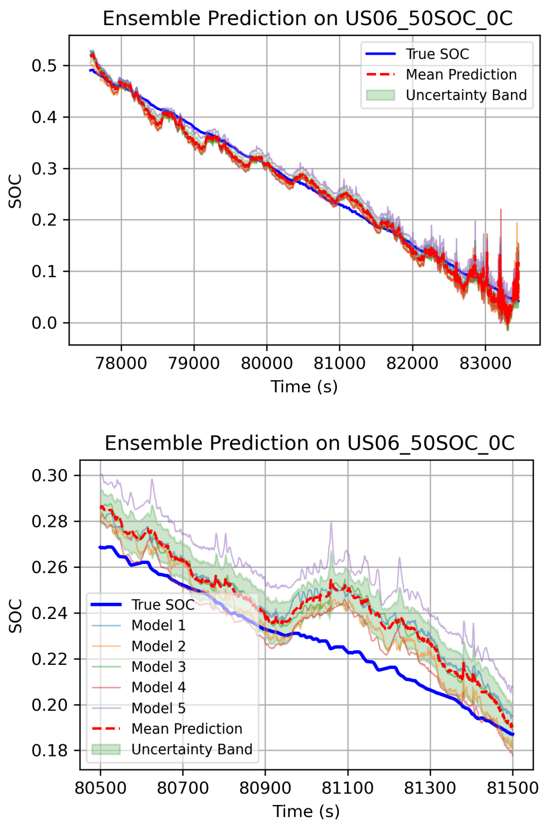
Fig. 4. SOC estimation by different GRU-based models

Table 1. RMSE and MAE (%) comparison of models on test datasets

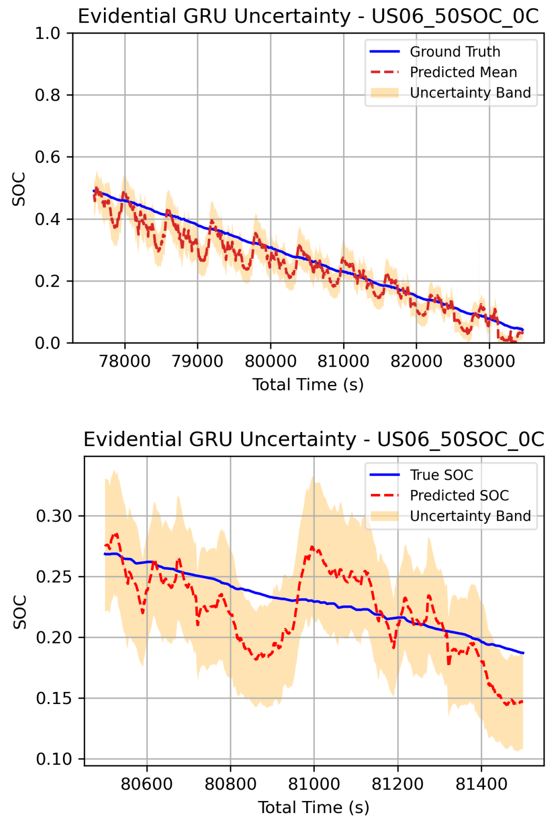
RMSE (%)			
Test Dataset	**Single**	**Ensemble**	**Evidential**
DST_50SOC_0C	1.10	0.78	**0.62**
FUDS_80SOC_0C	**1.55**	1.71	3.81
BJDST_80SOC_0C	3.78	**3.08**	6.4
US06_50SOC_0C	1.56	**1.51**	4.31
US06_80SOC_0C	3.80	**2.50**	5.14
MAE (%)			
Test Dataset	**Single**	**Ensemble**	**Evidential**
DST_50SOC_0C	0.92	0.59	**0.50**
FUDS_80SOC_0C	**1.26**	1.47	2.93
BJDST_80SOC_0C	3.33	**2.83**	5.37
US06_50SOC_0C	1.28	**1.23**	3.45
US06_80SOC_0C	3.65	**2.29**	4.26
Inference Time(ms/sequence, approx.)			
Device	**Single**	**Ensemble**	**Evidential**
Intel Core i9-13900 (CPU)	0.25	1.25	**0.25**

For uncertainty estimation, we train five individual models on overlapping subsets of the training data. These models produce both individual predictions and an ensemble prediction, along with a baseline uncertainty band, as illustrated in Figure 5a. Subsequently, we train an evidential regression model to learn the parameters of the Normal-Inverse-Gamma (NIG) distribution. Initially, the predicted uncertainty band is relatively wide, but it can be calibrated by fine-tuning the hyperparameter λ. Figure 5b presents the total uncertainty band obtained using $\lambda = 0.001$.

Additionally, we find that when trained on clean data, the model poorly learns the β parameter, resulting in negligible variance in the data-driven (aleatoric) uncertainty. To address this, we inject Gaussian noise into the input features—current, voltage, and temperature—using controlled standard deviations relative to the normalized data scale (e.g., $\sigma_{\text{Current}} = 0.1$, $\sigma_{\text{Voltage}} = 0.05$, $\sigma_{\text{Temperature}} = 0.04$). This augmentation enhances input variability and

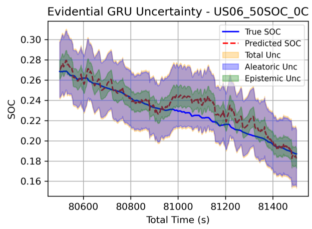


(a) Model ensemble

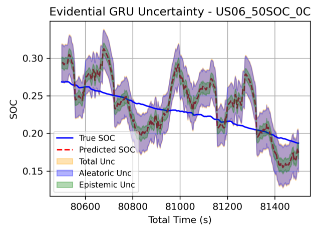


(b) Evidential regression

Fig. 5. Uncertainty estimation comparison between ensemble and evidential regression method



(a) Training without noise



(b) Training with noise

Fig. 6. Tuning of evidential uncertainty taking ensemble method as baseline

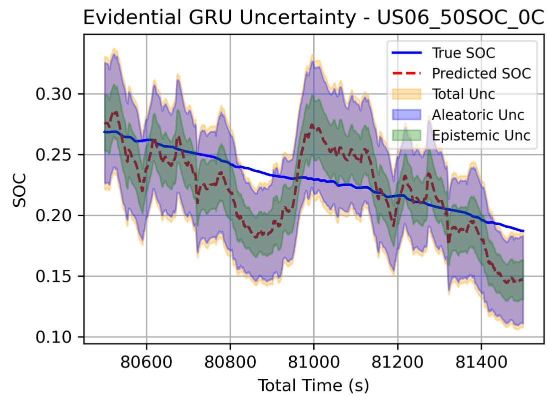


Fig. 7. Epistemic and aleatoric uncertainty band estimated by evidential regression framework

encourages the model to capture inherent measurement uncertainties better as demonstrated in Figure 6.

Following noise injection, we observe meaningful learning of β, with increased values reflecting improved aleatoric uncertainty capture as illustrated in Figure 7. These results demonstrate that controlled noise injection effectively stimulates uncertainty learning while maintaining accurate SOC predictions. It is important to note that noise-driven uncertainty learning entails a trade-off, with higher RMSE observed on out-of-distribution data. Nevertheless, for in-distribution scenarios, the performance remains comparable to that of the ensemble method, despite its lower computational complexity.

5. DISCUSSION AND FUTURE WORK

This work presents a computationally efficient framework for estimating battery state-of-charge (SOC) along with associated uncertainties. The proposed model provides not only total uncertainty estimates but also a clear decomposition into data-driven (aleatoric) and model-driven (epistemic) uncertainties. While evidential regression enables significantly faster inference compared to ensemble methods, it requires careful tuning of the regularization parameter λ and incurs a slightly higher RMSE, specifically for out-of-distribution data. Nonetheless, for in-distribution data, evidential regression achieves performance comparable to ensemble approaches, making it an attractive solution for real-time SOC estimation where computational efficiency is critical.

5.1 Future Work:

In real-world settings, sensor inputs for SOC estimation are often corrupted by non-Gaussian noise arising from environmental variability and hardware limitations. To enhance estimation reliability, we plan to integrate a particle filter (PF) that treats the GRU output as a noisy measurement model and propagates particles using a Coulomb counting-based transition model. At each time step, the PF resamples particles based on their normalized weights, reflecting the likelihood of each particle given the GRU prediction.

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