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RESEARCH ARTICLE

Enhancing the Sustainability of Underground Battery Storage: A Robust SOC Estimation Model Against Thermal Variations for Green Energy Systems

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Abstract

The widespread adoption of Battery Energy Storage Systems (BESS) is crucial for integrating intermittent renewable sources like solar and wind into the power grid, thereby advancing the goals of green energy. Deploying BESS underground offers a sustainable solution to land constraints and safety concerns. However, the dynamic and complex thermal environment underground severely challenges the accurate State-of-Charge (SOC) estimation, which is vital for the safety, longevity, and operational efficiency of BESS. Data-driven SOC models often suffer from performance degradation due to data distribution shifts caused by temperature fluctuations, especially when operational data for specific underground temperatures is sparse. To tackle this issue, this paper proposes a transfer learning model based on adversarial domain adaptation. The model utilizes a Gated Recurrent Unit (GRU) network for feature extraction and incorporates a Gradient Reversal Layer (GRL) to learn temperature-invariant features through an adversarial training mechanism. This approach effectively transfers knowledge from a data-rich source domain (standard temperature) to data-sparse target domains (varied underground temperatures). Comprehensive experiments on a public battery dataset covering a wide temperature range (-20 °C to 40 °C) demonstrate that our method significantly reduces SOC estimation errors under unseen thermal conditions compared to conventional models. The proposed solution enhances the reliability and sustainability of underground BESS, contributing to more resilient and efficient green energy infrastructure.

Keywords: underground energy storage, battery energy storage system (BESS), state-of-charge (SOC) estimation, adversarial domain adaptation, transfer learning.

1 Introduction

The impetus for the global transition to renewable energy stems from the urgent need to combat climate change and enhance long-term environmental sustainability [1]. However, the intermittent nature of primary renewable energy sources such as solar and wind poses significant challenges to the stable and reliable operation of power grids [2]. Battery

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Energy Storage Systems (BESS), with their rapid response capabilities and flexible scalability, play a pivotal role in smoothing renewable energy fluctuations and managing grid peak loads, emerging as a core technology to address this challenge [3]. The deployment of BESS faces issues including land scarcity, safety hazards, and environmental impacts [4]. Land use constraints and societal safety concerns have driven the deployment of BESS underground. Underground BESS installations offer several notable advantages, particularly in improved thermal management and enhanced safety, while effectively addressing surface space limitations [5, 6].

However, deploying BESS underground introduces a new and complex set of thermoelectric challenges. The subterranean environment is not thermally stable but dynamic, governed by subsurface heat transfer and continuously influenced by ambient thermal disturbances [7]. The continuous operation of batteries leads to gradual heat accumulation, altering the local temperature field over time [8]. The thermal field of the underground environment is a complex dynamic system, its characteristics determined by the coupling of multiple factors such as site geology, hydrogeological conditions, surface temperature fluctuations, and the heat generation of the storage system itself, and is co-dominated by both conduction and convection mechanisms [9]. This implies that even without BESS operation, the inherent properties of the geological medium and changes in the external environment can cause dynamic variations in the underground temperature field.

In application scenarios such as Smart Distribution Networks (SDNs), the State of Charge (SOC) estimation of BESS is critical for the control and operation of the entire power system [10]. Inaccurate SOC estimation can trigger a cascade of failures, from Battery Management System (BMS) operational errors to market defaults, not only compromising the safety and economic viability of the battery asset but also potentially jeopardizing the stability of the entire grid [11]. Traditional data-driven SOC models exhibit suboptimal performance in these underground applications, as their efficacy degrades significantly when operating temperatures deviate from the training conditions [12]. This performance degradation is a classic example of the domain shift problem in machine learning, where a model trained on data from one environment (the source domain) fails to generalize to another (the target domain).

To address the limited generalization ability of SOC estimation models caused by differences in data distribution between the source and target domains, many studies in recent years have introduced domain adaptation (DA) techniques to enhance model performance in the target domain. Bao et al. [13] proposed an adversarial domain adaptation network (LSTM-DA) that uses a Gradient Reversal Layer (GRL) and a domain discriminator. Through adversarial training, this approach enables the feature extractor to learn invariant features between the source and target domains, thereby improving the model's estimation accuracy in the target domain. Liu et al. [14] presented an unsupervised domain adaptation framework for SOC estimation across different operating conditions. By combining Maximum Mean Discrepancy (MMD) with adversarial training, their method explicitly aligns the feature distributions of the source and target domains, reducing the model's generalization error in the target domain. Ni et al. [15] proposed a Deep Domain Adaptation Network (DDAN) for SOC transfer learning between different battery types. By integrating a domain-adversarial mechanism with MMD, this method explicitly addresses the bias in feature distributions between the source and target domains, thereby improving the model's estimation consistency across different battery types.

This paper proposes a transfer learning model for SOC estimation based on adversarial domain adaptation. The model employs a Gated Recurrent Unit (GRU) network to extract features from the battery's operational data and utilizes a Gradient Reversal Layer (GRL) to learn temperature-invariant features through an adversarial training mechanism. This approach enables robust and accurate SOC estimation amidst the wide temperature fluctuations characteristic of underground storage environments, without requiring extensive data from every possible thermal condition.

2 Model

The overall structure of the proposed adversarial domain adaptation-based SOC estimation model is shown in Figure 1. It consists of a feature extraction module, an SOC regression layer, and a domain discrimination module (Domain Discriminator). The feature extraction module is used to extract high-dimensional feature representations from the raw battery data; the SOC regression layer outputs the battery's SOC estimate from the extracted features; and the domain discrimination module

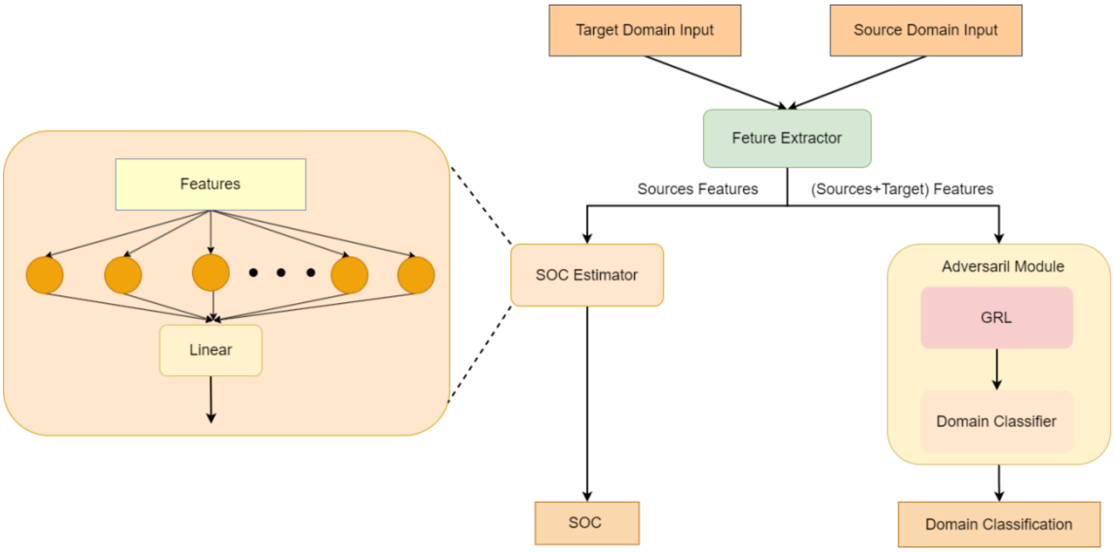

Figure 1. The overall structure of the proposed adversarial domain adaptation-based SOC estimation model.

comprises a Gradient Reversal Layer (GRL) and a domain classifier, which aims to narrow the feature distribution gap between the source and target domains through adversarial training. In this way, the model learns general features that are insensitive to temperature variations, thereby effectively leveraging the knowledge from the data-rich source domain.

2.1 Feature Extractor (GRU Network)

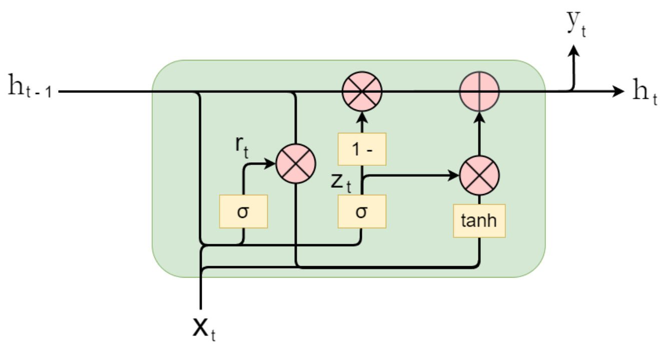

Figure 2. GRU cell.

The model employs a Gated Recurrent Unit (GRU) neural network as the core feature extractor, as shown in Figure 2. GRU, as a variant of Recurrent Neural Networks (RNNs), introduces an update gate and a reset gate to control the information flow [16]. The gating mechanism is defined as:

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \tag{1}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{2}$$

where z_t is the update gate at time step t (controlling how much of the previous hidden state is retained), and r_t is the reset gate (adjusting the influence of the previous hidden state on the current input). $\sigma(\cdot)$ denotes the sigmoid activation function; W_r and U_r are the weight matrices for the inputs and hidden state; x_t is the input vector at time t; and h_{t-1} is the previous time step's hidden state.

Subsequently, the GRU hidden state is updated as follows:

$$h_t = z_t \circ h_{t-1} + (1 - z_t) \circ \tanh\left(W_h x_t + U_h (r_t \circ h_{t-1})\right) \tag{3}$$

where h_t is the updated hidden state, $\circ$ denotes element-wise multiplication, and $\tanh(\cdot)$ is the hyperbolic tangent activation function.

With the gating mechanism, GRU effectively mitigates the long-sequence dependency problem and has fewer parameters and faster training speed compared to LSTM. This feature extractor processes the battery sensor sequences, captures the temporal dynamics and nonlinear relationships, and uses the hidden state at the final time step of the sequence as a compact feature representation of the entire sequence.

2.2 SOC Regression Layer

This module is a simple fully connected layer that maps the feature vector output by the feature extractor to a single SOC prediction value. After the linear transformation by this fully connected regression layer, we obtain an estimate of the battery's state of charge for the current input sequence. The SOC regression loss uses the mean squared error (MSE), formulated as:

$$L_{SOC} = \frac{1}{N}\sum_{i=1}^{N}\left(SOC_i^{act} - SOC_i^{pred}\right)^2 \quad (4)$$

2.3 Domain Discrimination Module

To achieve cross-domain transfer learning, the model introduces a domain-adversarial training mechanism. This module consists of a Gradient Reversal Layer (GRL) and a domain classifier. By introducing the GRL to implement adversarial training, the feature extraction network is compelled to learn domain-invariant discriminative features [17]. The GRL is placed between the feature extraction sub-network and the domain classifier sub-network. In forward propagation, the GRL does not alter the input features (i.e., the output is identical to the input):

$$h = f \quad (5)$$

where f is the feature vector output from the feature extraction network, and h is the feature representation passed to the domain classifier after the GRL. During backpropagation, the GRL multiplies the gradient signal by a fixed negative coefficient to achieve gradient reversal. This can be expressed as:

$$\frac{\partial L_{dom}}{\partial f} = -\lambda\frac{\partial L_{dom}}{\partial h} \quad (6)$$

which indicates that the gradient of the domain classification loss L_{dom} with respect to the input features is reversed in direction, and λ is the magnitude of this negative scaling factor.

Through this mechanism, the GRL places the feature extraction network and the domain classifier in adversarial objectives: it forces the feature extractor to adjust its parameters in a direction that increases the domain classification error, thereby confusing the domain classifier.

The domain classifier is a multilayer perceptron (MLP) composed of two fully connected layers with ReLU activation, and its final output layer has a number of nodes equal to the number of domain categories. The domain classifier receives the feature vector after the GRL and attempts to predict which domain (source or target) the feature comes from. During adversarial training, the domain classifier strives to distinguish between source-domain and target-domain samples as accurately as possible. However, due to the presence of the GRL, the feature extractor is simultaneously optimized to make the domain classifier's job as difficult as possible – in other words, to learn features that are indistinguishable between the source and target domains. Domain discrimination is essentially a multi-class classification task, and we use the multi-class cross-entropy as the domain classification loss:

$$L_{dom} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{K} d_{ij}\ln\hat{d}_{ij} \quad (7)$$

where K is the number of domain categories; $d_{ij} = 1$ if the i-th sample belongs to the j-th domain (and $d_{ij} = 0$ otherwise); and $\hat{d}_{ij}$ is the predicted probability that the i-th sample belongs to the j-th domain.

In summary, the feature extractor, SOC regression layer, and domain discrimination module work together in this model. This design ensures accurate battery SOC estimation while extracting features that are insensitive to differences between domains, thereby enhancing the model's generalization performance across different data domains.

3 Experimental Validation and Discussion

3.1 Dataset Description

To simulate the operational characteristics of underground energy storage systems in a dynamic thermal environment, this study uses a public dataset for experimental validation. In the experiments, we utilize the LGHG2 battery dataset [18] created by Phillip Kollmeyer's team at McMaster University. This dataset contains battery operating data collected at ambient temperatures of 40 °C, 25 °C, 10 °C, 0 °C, -10 °C, and -20 °C. This wide temperature gradient makes it an ideal choice for simulating the thermal stress faced by underground BESS in different geographical locations, seasons, and under various operational loads. We select the mixed driving cycles Mixed 1 through Mixed 8 as our experimental dataset; each mixed cycle is a random combination of four standard automotive driving cycles (UDDS, HWFET, LA92, and US06). Specifically, 25 °C is designated as the source domain. Mixed1 and Mixed2 at 25 °C are used as the test set, and the remaining data at 25 °C serves as the training set for the source domain. Each of the other temperatures serves as a target domain; for each target temperature, one Mixed cycle is chosen as the target domain training set, and two Mixed cycles from the remaining data are selected as the test set.

3.2 Evaluation Metrics

After training, the model's predictions on the test datasets are evaluated using RMSE and MAE. Their calculation formulas are as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{SOC}_t^{\mathrm{act}} - \mathrm{SOC}_t^{\mathrm{pred}}\right|_{\omega} \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\mathrm{SOC}_t^{\mathrm{act}} - \mathrm{SOC}_t^{\mathrm{pred}}\right)_{\omega}^{2}} \tag{9}$$

MAE computes the mean absolute difference between the predicted values and the actual values, representing the average magnitude of the prediction error (a smaller value indicates better model performance). RMSE is one of the most common evaluation metrics for regression models; it measures the magnitude of the error between the model's predictions and the true labels, with larger errors contributing more heavily to the metric.

3.3 Experimental Design

In this experiment, a sliding window mechanism is used for data segmentation, with a window length of 50 and a step size of 10. Meanwhile, the training datasets at 40 °C, 25 °C, 10 °C, 0 °C, -10 °C, and -20 °C are labeled with domain IDs from 0 to 5, respectively, to distinguish different temperature conditions. During the transfer learning stage, we adopt a strategy of freezing all other layers and fine-tuning only the SOC regression layer.

To verify the effect of the domain-adversarial training strategy on improving the model's cross-domain generalization ability, and to determine whether fine-tuning after adversarial pre-training is superior to direct fine-tuning, we design the following comparative experiments:

- Baseline1: The model is trained using only source domain (25 °C) data without any domain adaptation, and the trained model is then directly evaluated on the target domain data. This serves as a baseline to assess the model's generalization performance in the absence of cross-domain adaptation.
- Baseline2: Fine-tuning the Baseline1 model on target domain data. Specifically, the trained Baseline1 model (from the source domain) is loaded, its feature extraction layers are kept fixed, and only the final regression output layer is fine-tuned using the labeled data from the target domain. This experiment evaluates the performance gain obtained by directly fine-tuning the model with a small amount of target domain labeled data.
- MethodA: A cross-domain method using domain-adversarial training. During training, both labeled source domain data and unlabeled target domain data are used simultaneously. By introducing a Gradient Reversal Layer (GRL) and a domain classifier into the model, the feature extraction network is encouraged to produce domain-invariant features, aligning the feature distributions of the source and target domains. MethodA employs a combined loss function mechanism, with the total loss defined as:

$$L = L_{SOC} + \lambda_d L_{\mathrm{domain}} \tag{10}$$

where L_{SOC} and L_{domain} denote the SOC regression loss and domain classification loss, respectively. To balance the magnitude of these two loss terms, the domain loss coefficient λ_d is dynamically updated during training according to the following strategy:

$$\lambda_d \leftarrow (1-\eta)\lambda_d + \eta\left(w_d \frac{\mathrm{EMA}(L_{SOC})}{\mathrm{EMA}(L_{\mathrm{dom}})}\right) \tag{11}$$

Where w_d is the domain loss alignment weight (set to 1 in our experiments, meaning that after weighting, the domain loss is kept on the same order of magnitude as L_{SOC}), $\mathrm{EMA}(\cdot)$ denote the exponentially smoothed values, and η is the update rate per epoch. This dynamic weighting mechanism is designed to constrain the weighted domain loss to the same order of magnitude as $w_d \times L_{SOC}$, thereby maintaining a balanced loss scale during adversarial training.

MethodA is designed to improve the model's cross-domain generalization ability through adversarial domain learning without using any actual SOC labels from the target domain.

- MethodB: This approach first uses MethodA to perform unsupervised adversarial domain pre-training on the combined source+target data, and then conducts supervised fine-tuning on the target domain data. Specifically, the model weights obtained from MethodA's pre-training are loaded, the model's feature extraction layers

Table 1. RMSE and MAE of different methods on the test sets under various ambient temperatures.

Methods	Metrics	Ambient Temperature 40 °C	25 °C	10 °C	0 °C	-10 °C	-20 °C
Baseline1	RMSE(%)	11.8	1.109	6.12	14.66	32.45	48.17
	MAE(%)	10.36	0.76	4.65	11.26	27.61	40.6
MethodA	RMSE(%)	4.31	1.22	4.12	6.14	11.17	19.59
	MAE(%)	3.56	0.86	3.18	4.75	9.49	16.12
Baseline2	RMSE(%)	5.13	∼	4.28	8.72	12.54	16.34
	MAE(%)	3.96	∼	3.17	6.94	10.02	13.38
MethodA	RMSE(%)	2.71	∼	3.12	4.22	6.05	9.69
	MAE(%)	1.98	∼	2.47	3.38	4.68	7.94

are frozen, and only the regression output layer is fine-tuned using the labeled target domain data; no adversarial loss is applied during the fine-tuning stage. This method is designed to combine the advantages of unsupervised domain alignment and supervised fine-tuning, by both enhancing the source-trained model's generalization to the target domain and further leveraging the target domain labels to refine the model's performance.

With the above experimental setup, we can clearly evaluate the role of each strategy. Comparing Baseline1 with MethodA tests whether introducing domain-adversarial training significantly improves the model's cross-domain generalization ability. Comparing Baseline2 with MethodB allows us to assess whether fine-tuning on top of adversarial pre-training is superior to directly fine-tuning a model that was pre-trained only on the source domain.

3.4 Experimental Results and Analysis

The prediction errors of the four experimental groups on the test sets at each temperature are shown in Table 1. The results show that as the test temperature diverges further from the source domain temperature, the SOC estimation error of each experimental group tends to increase. Baseline1 and MethodA achieve similar error levels at the source domain temperature, and both perform well under that condition. However, the Baseline1 model exhibits much larger errors at the target domain temperatures, especially at –10 °C and –20 °C. In contrast, MethodA's errors at the target domain temperatures are significantly lower than those of Baseline1. The Baseline2 and MethodB groups, which involve fine-tuning the SOC regression layer, achieve notable improvements on the target domains. Among them, MethodB attains the lowest RMSE and MAE in each temperature case, and its predictions are far more accurate than those of Baseline2. Baseline2's performance, on the other hand, is still limited by the quantity of labeled target domain data and the distribution differences.

The discrepancies in data distribution across different temperature domains are the primary cause of the performance differences observed among the strategies. The battery's voltage and current characteristics shift significantly at different ambient temperatures compared to those at the source domain temperature. As a result, a model trained only on the source domain struggles to adapt to target domain data, leading Baseline1 to exhibit high estimation errors when a temperature domain shift occurs. The domain-adversarial mechanism introduced in MethodA forces the feature representations of the source and target domains to become aligned. In this way, without using any target domain labels, the model enhances its ability to identify common features across different temperatures, effectively mitigating the impact of the temperature domain shift and yielding lower errors on the target domain.

The fine-tuning strategy leverages a small amount of real target-domain labels to calibrate the model. By further training on target domain data, the model can learn the target domain's unique patterns, thereby significantly reducing the estimation bias. MethodB combines both adversarial domain alignment and fine-tuning: it uses unlabeled data to align the feature distributions between domains and a small number of labeled data to finely calibrate the model's output. This allows the model to maintain a low error even when target domain labels are limited. Nevertheless, even MethodB retains some prediction error, which may be attributed to the inherent complexity of battery SOC prediction, measurement noise, as well as the model not yet fully capturing certain detailed characteristics under extreme conditions.

4 Conclusion

Accurate and reliable State of Charge (SOC) estimation is a cornerstone for ensuring the safety, maximizing the lifespan, and improving the operational efficiency of Battery Energy Storage Systems (BESS), which are indispensable components for the widespread utilization of renewable energy. This paper addresses the critical challenge of performance degradation in SOC estimation for underground BESS caused by complex and dynamic thermal environments. We proposed and validated a novel transfer learning method based on adversarial domain adaptation. The core innovation of this approach lies in its ability to leverage a domain-adversarial training mechanism, enabling the GRU-based feature extractor to learn generalized, temperature-invariant feature representations. This allows the model to maintain high estimation accuracy even when target-domain operational data is severely limited.

Experimental results demonstrate that our proposed method (MethodA) significantly enhances the model's cross-temperature generalization capability without requiring any labeled target-domain data, outperforming the baseline model trained solely on standard temperature data. Furthermore, the combined strategy (MethodB), which integrates unsupervised adversarial pre-training with supervised fine-tuning using minimal target-domain labels, proves to be more effective in leveraging scarce labeled data than direct fine-tuning alone. This finding is particularly valuable for real-world green energy applications where collecting extensive labeled data under every possible operating condition is often impractical and costly.

By effectively aligning feature distributions across different thermal domains, our method provides a robust solution to mitigate the data drift problem induced by temperature variations and data sparsity in underground energy storage settings. This research not only contributes an advanced intelligent algorithm for BMS but also paves the way for more reliable, sustainable, and economically viable underground battery storage solutions. Ultimately, such technological advancements are vital for building resilient power grids with high penetration of renewables, supporting the global transition towards a sustainable energy future.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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