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Enhancing Lithium-Ion Battery State-of-Charge Estimation Across Battery Types via Unsupervised Domain Adaptation

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Abstract

Accurate estimation of the state-of-charge (SOC) in lithium-ion batteries (LIBs) is paramount for the safe operation of battery management systems. Despite the effectiveness of existing SOC estimation methods, their generalization across different battery chemistries and operating conditions remains challenging. Current data-driven approaches necessitate extensive data collection for each battery chemistry and operating condition, leading to a costly and time-consuming process. Hence, there is a critical need to enhance the generalization and adaptability of SOC estimators. In this paper, we propose a novel SOC estimation method based on Regression-based Unsupervised Domain Adaptation. We evaluate the performance of this method in cross-battery and cross-temperature SOC estimation scenarios. Additionally, we conduct a comparative analysis with a widely-used classification-based unsupervised domain adaptation approach. Our findings demonstrate the superiority of the regression-based unsupervised domain adaptation method in achieving accurate SOC estimation for batteries.

1. Introduction

Accurate real-time estimation of the state-of-charge (SOC) in batteries holds paramount importance across various domains, including electric vehicles and renewable energy storage systems. The SOC represents the percentage of remaining capacity, serving as a pivotal indicator of the battery's condition for facilitating effective operations.

Precise SOC estimation is imperative for optimizing energy utilization and mitigating premature degradation, consequently reducing maintenance costs and environmental impacts. However, SOC determination poses a formidable challenge due to its dependence on multiple interconnected variables such as voltage, current, resistance, and temperature, complicating precise estimation (Z. Wang, Feng, Zhen, Gu, & Ball, 2021). Thus, the development of robust and adaptable SOC estimation methods is essential to meet the escalating demand for sustainable energy solutions. Conventional SOC estimation approaches often falter in dynamic environments characterized by temperature variations, load fluctuations, and battery aging. Compounding this challenge is the diverse array of battery types with varying chemistries. Conventional methods necessitate significant investments in time and resources to acquire labeled data specific to each battery variant for accurate SOC estimation. Consequently, there arises a crucial need for innovative, adaptable SOC estimation methods capable of addressing these challenges while reducing reliance on expensive labeled data sources.

Numerous methodologies have been proposed for SOC estimation, employing diverse sensor data and modeling techniques. Traditional approaches, such as look-up table methods and direct-counting methods, often rely on simple algorithms but struggle with real-time estimation due to their requirement for stable discharge currents (Shen, Li, Meng, Zhu, & Shen, 2023). Conversely, model-based methods address this limitation but demand prior knowledge of battery characteristics, rendering them less suitable for dynamic and varied operational conditions. Recent advancements have introduced data-driven methods, which eschew reliance on domain knowledge and instead utilize battery parameters such as current, voltage, and temperature measurements to develop SOC estimators. Various data-driven techniques have been proposed for battery SOC estimation. (Li, Wang, & Gong, 2016; Hu et al., 2014; Tong, Lacap, & Park, 2016; Khumprom & Yodo, 2019; Chandra Shekar & Anwar, 2019). How et al. offer a comprehensive review of SOC estimation methods (How, Hannan, Lipu, & Ker, 2019). The primary drawback of data-driven approaches lies in their dependence on substantial training data, which can be expensive and time-intensive to acquire. In response to the challenge of limited data, transfer learning (TL) has emerged as a potent technique in machine

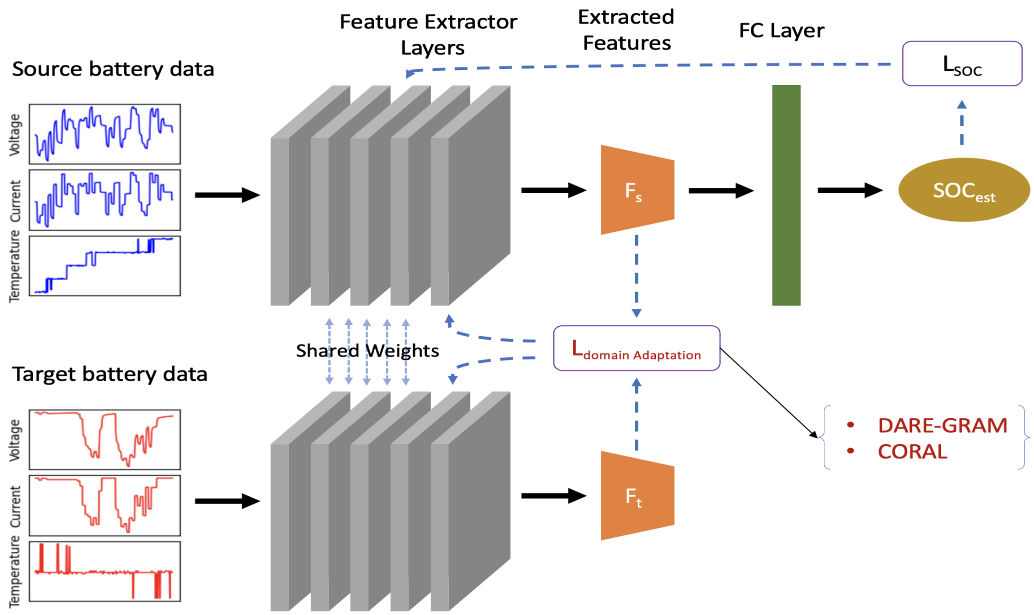

Figure 1. Structure of the Proposed Deep Neural Network Architecture for SOC Estimation using Domain Adaptation.

learning.

In the realm of battery SOC estimation, transfer learning holds promise by leveraging existing data from one domain (e.g., a specific battery type or environment), known as the source domain, to enhance SOC estimation performance in a different, less well-characterized domain, referred to as the target domain. Fine-tuning, the most popular TL approach, involves further training a pre-trained neural network model, originally trained on a large dataset for a different domain, using a smaller dataset specific to the target domain. Fine-tuning has recently been applied to battery SOC estimation to transfer knowledge between different ambient temperatures of the same battery type (Y.-X. Wang, Chen, & Zhang, 2022), or between different battery types (Bhattacharjee, Verma, Mishra, & Saha, 2021). However, fine-tuning necessitates access to labeled examples from the target domain, which may not always be readily available. In the case of lithium-ion batteries (LIBs), obtaining reliable labeled data under real-world conditions is particularly challenging.

To address the challenge of lacking labeled data for the target domain, machine learning researchers have introduced Unsupervised Domain Adaptation (UDA). Originating in the computer vision domain, UDA tackles the broader issue of transferring knowledge from a source domain to a target domain where labeled data is scarce (Long, Cao, Wang, & Jordan, 2015). This is particularly pertinent in scenarios where the characteristics of the target domain evolve over time, diverging from the source domain, and making traditional supervised learning approaches inadequate. Batteries are subjected to diverse environmental conditions, undergo degradation over time, and witness frequent introductions of new battery chemistries. A central strategy of UDA techniques is to generate domain-invariant feature representations by aligning feature distributions between domains (Wilson & Cook, 2020). This facilitates model adaptation to new and dynamically changing environments, enabling effective generalization without access to labeled data in the target domain.

A common approach for generating domain-invariant feature representations is to minimize a divergence measured as the distance between distributions. Maximum mean discrepancy (MMD) (Borgwardt et al., 2006), multi-kernel MMD (MK-MMD) (Gretton et al., 2012), and lastly, correlation alignment (CORAL) (Sun & Saenko, 2016) are among the popular divergence minimization techniques. Recently, there has been growing interest in applying UDA techniques to estimate battery SOC (Shen, Li, Liu, Zhu, & Shen, 2022; Bian, Yang, & Miao, 2020; Oyewole, Chehade, & Kim, 2022; Ni, Li, & Yang, 2023; Meng, Agyeman, & Wang, 2023). While these UDA techniques were initially developed for classification tasks, SOC estimation poses a regression task. A significant distinction between regression and classification problems is that regression problems are less robust to feature scaling, potentially impacting model robustness when aligning feature distributions with UDA methods (Chen, Wang, Wang, & Long, 2021).

To address this challenge, a specialized domain adaptation method for regression problems has emerged. DARE-GRAM (Nejjar, Wang, & Fink, 2023) is one such recent domain adaptation regression (DAR) technique motivated by the closed-form solution of ordinary least squares (OLS). Unlike pre-

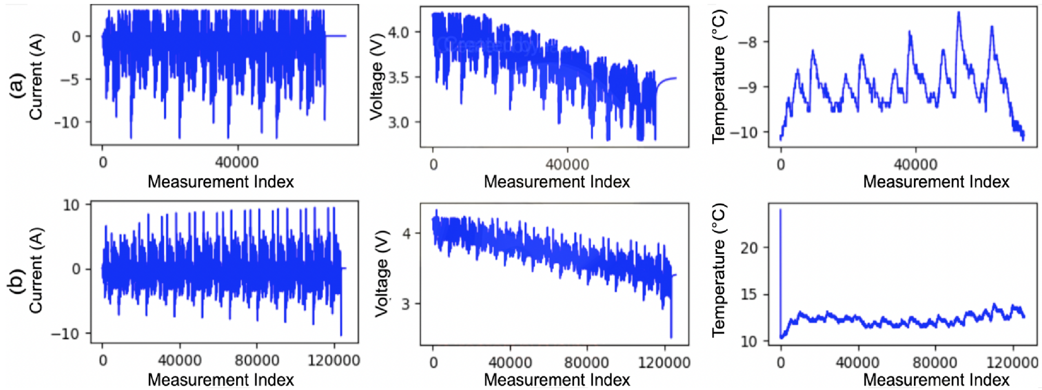

Figure 2. Measured Current, Voltage, and Battery Temperature During LA92 Drive Cycle. (a) Panasonic LiB and (b) LG LiB.

viously discussed classification-based methods that directly align features, DARE-GRAM aligns the inverse Gram matrix of the features. The authors demonstrated the capability and robustness of this method through experiments on three benchmark computer vision regression datasets.

In this paper, we explore the application of unsupervised domain adaptation (UDA) techniques within the framework of transfer learning (TL) to enhance the precision of battery State of Charge (SOC) estimation. We conduct a comparative study between a well-established classification-based domain adaptation method (CORAL) and DARE-GRAM, a regression-based method, marking the first application of a regression-based UDA method to battery management tasks, to the best of our knowledge. We examine their efficacy across a range of TL tasks and settings, aiming to provide comprehensive insights into their performance and suitability for addressing the complex challenges posed by evolving battery landscapes and diverse operational conditions.

The remainder of this paper is organized as follows. Section 2 presents the proposed methodology. Section 3 elucidates the LiB datasets and implementation details. Section 4 offers the experimental results and discussion. Finally, Section 5 concludes the paper.

2. Methodology

2.1. Problem Statement

We begin by defining the problem of cross-battery state-of-charge (SOC) estimation. The source domain D^s represents the battery type with labeled data $X^s = \{x_j^s, y_j^s\}_{j=1}^{n_s}$, where n_s denotes the number of source samples. Conversely, the target domain D^t represents the battery type with unlabeled data $X^t = \{x_j^t\}_{j=1}^{n_t}$, where n_t represents the number of target samples. x_j^s and x_j^t are the temporal measurements of voltage, current, and temperature for both source and target batteries until the current time-step, each with a length of l. Additionally, y_j^s represents the SOC at the current time-step for sample j. Specifically, each sample comprises previous voltage, current, and temperature measurements from time-step $k - l + 1$ to the current time-step k as input, with the SOC of the current time-step k as the label. This paper aims to establish an SOC estimation model to predict the SOC of the target battery y_j^t utilizing source data X^s and target data X^t, assuming the existence of a distribution discrepancy between the source and target data.

2.2. Deep Neural Network

Our approach leverages a deep neural network architecture to tackle the intricate task of state-of-charge (SOC) estimation. The architecture of our proposed network is depicted in Figure 1, comprising two main modules: a feature extractor and a predictor. The feature extractor plays a pivotal role in capturing the temporal dynamics and patterns inherent in the battery data, facilitating the extraction of informative features crucial for precise SOC estimation. This module may encompass convolutional layers in convolutional neural networks (CNNs), recurrent layers in recurrent neural networks (RNNs), or fully connected layers in feedforward neural networks. Each type of feature extractor possesses distinct strengths and weaknesses, and their performance can vary depending on the specific problem at hand. Subsequently, the extracted features are propagated through a fully-connected layer with a single output node, tasked with mapping these features to the SOC estimation.

2.3. Domain Adaptation

Unsupervised Domain Adaptation (UDA) techniques can be instrumental in mitigating the domain discrepancy between source and target domains. These methods facilitate the alignment of feature distributions across domains, thereby enabling the effective transfer of knowledge from the source domain to enhance state-of-charge (SOC) prediction in the target domain. Metric-based UDA methods aim to alleviate cross-domain distribution discrepancies by applying static criteria. In this study, we leverage a classification-based UDA method, CORAL, and a regression-based UDA method, DARE-GRAM.

Table 1. Results of BiGRU Network for Different Domain Adaptation Methods: Panasonic Battery as Source Domain and LG Battery as Target Domain

Source Temp.	Target Temp.	No TL		CORAL		DARE-GRAM	
		MSE	MAE	MSE	MAE	MSE	MAE
-20°C	-20°C	0.093	0.252	0.103	0.266	**0.031**	**0.143**
	-10°C	0.156	0.342	0.097	0.270	**0.018**	**0.105**
	0°C	0.368	0.522	0.182	0.342	**0.017**	**0.106**
	10°C	0.354	0.513	0.195	0.357	**0.091**	**0.260**
	25°C	0.358	0.516	0.184	0.348	**0.090**	**0.260**
-10°C	-20°C	0.089	0.257	0.025	0.134	**0.018**	**0.110**
	-10°C	0.031	0.148	0.037	0.161	**0.016**	**0.100**
	0°C	0.134	0.305	0.016	0.107	**0.009**	**0.075**
	10°C	0.354	0.513	0.040	0.150	**0.008**	**0.071**
	25°C	0.356	0.514	**0.007**	**0.075**	0.086	0.256
0°C	-20°C	0.049	0.167	0.046	0.162	**0.034**	**0.146**
	-10°C	0.015	0.106	**0.007**	**0.07**	0.008	0.066
	0°C	0.018	0.114	0.013	0.101	**0.005**	**0.057**
	10°C	0.018	0.099	**0.004**	**0.05**	0.011	0.077
	25°C	0.028	0.131	**0.003**	**0.044**	0.02	0.122
10°C	-20°C	0.415	0.56	0.164	0.344	**0.102**	**0.28**
	-10°C	0.376	0.53	0.153	0.324	**0.067**	**0.219**
	0°C	0.366	0.521	0.046	0.192	**0.013**	**0.091**
	10°C	0.03	0.154	0.028	0.151	**0.003**	**0.046**
	25°C	0.009	0.071	**0.005**	**0.065**	0.006	0.068

Correlation Alignment (CORAL) (Sun & Saenko, 2016) stands as a potent domain adaptation technique designed to align the second-order statistics of both the source and target domains. Its primary objective is to diminish the distribution discrepancy between these domains by matching their covariances. This process involves whitening the source and target data to eliminate disparities in variances and subsequently re-coloring the source data to align with the color (covariance) of the target data. By aligning these statistical properties, CORAL effectively enhances the similarity between the source and target distributions, thereby bolstering the transferability of models from the source domain to the target domain. CORAL demonstrates particular efficacy in scenarios where distribution shifts predominantly stem from alterations in data covariances.

DARE-GRAM (Nejjar et al., 2023) harnesses the power of the inverse Gram matrix to align the feature space, taking into consideration the discriminative capability of the final linear layer. This approach prioritizes angle alignment and scale alignment to foster greater compatibility between the source and target domains. The underlying motivation is to identify a feature space conducive to facile learning by a shared linear regressor. Leveraging the ordinary least-squares (OLS) closed-form solution, the method estimates the parameters of the linear layer for regression purposes. By emphasizing the alignment of the angle and scale of the inverse Gram matrix, DARE-GRAM presents a more stable and robust approach compared to direct feature alignment. DARE-GRAM loss function is expressed as follows:

$$L_{DAREGRAM}(F_s, F_t) = \alpha L_{cos}(F_s, F_t) + \gamma L_{scale}(F_s, F_t) \quad (1)$$

where F_s and F_t are extracted features from the source and target domains, respectively. α and γ are hyper-parameters governing the influence of angle and scale alignment, respectively. $L_{cos}(F_s, F_t)$ corresponds to angle alignment, aiming to maximize the cosine similarity between the F_s and F_t. Meanwhile, $L_{scale}(F_s, F_t)$ represents the scaling alignment term, endeavoring to minimize the discrepancy between the k-principal eigenvalues, where k is selected using a specified threshold.

2.4. Training Process

During the training phase, we leverage both source and target data to cultivate domain-invariant representations. The network is guided by two distinct loss functions: the SOC prediction loss, aimed at minimizing the disparity between predicted and actual SOC values in the source domain, and the domain alignment loss, which mandates the resemblance of feature distributions between the source and target domains. The synergy of these loss functions ensures that the network acquires both precise SOC prediction capabilities and domain-invariant features, thereby augmenting SOC estimation accuracy in the target domain. The total loss of the deep network in an end-to-end training scenario is subsequently computed as follows:

$$L_{total} = L_{SOC} + L_{DomainAdaptation} \quad (2)$$

where L_{SOC} denotes the prediction loss, and $L_{DomainAdaptation}$ represents the domain adaptation loss. Since both L_{SOC} and $L_{DomainAdaptation}$ losses are equally critical to the success of the model, we set equal weights to both losses to prevent either loss from dominating. We employ two domain adaptation methods introduced in the previous section to calculate the domain adaptation loss.

3. Experimental Setup

3.1. Dataset Description

In this study, the efficacy of the proposed method is evaluated using two publicly available LiB datasets: 1) the Panasonic 18650PF dataset (Kollmeyer, 2018) acquired from the University of Wisconsin–Madison, and 2) the LG 18650HG2 dataset (Naguib, Kollmeyer, & Skells, 2020) obtained from McMaster University in Hamilton, Ontario, Canada.

For the Panasonic 18650PF dataset, testing involved brand-new 2.9Ah Panasonic 18650PF cells in an 8 cu.ft. thermal chamber, utilizing a 25 amp, 18 volt Digatron Firing Circuits Universal Battery Tester channel. Similarly, for the LG 18650HG2 dataset, testing was conducted with brand-new 3Ah LG HG2 cells in an 8 cu.ft. thermal chamber, employing a 75 amp, 5 volt Digatron Firing Circuits Universal Battery Tester channel. Both datasets encompassed a series of drive cycles, including US06, HWFET, UDDS, and LA92, performed for each battery. Notably, the battery tests in both datasets were conducted at discrete ambient temperatures ranging from -20°C to 25°C. Figure 2 illustrates the voltage, current, and battery temperature measurements of the two batteries during the LA92 drive cycle.

3.2. Implementation Details

The Panasonic and LG batteries are designated as the "source" and "target" batteries, respectively. Specifically, each experiment involves one Panasonic battery type under a particular ambient temperature serving as the source domain, while LG battery type under a different ambient temperature acts as the target domain. The target data is evenly partitioned into training and testing sets, with the training set utilized for domain adaptation and the testing set employed for performance assessment. As our objective is to assess the efficacy of various unsupervised domain adaptation methods for near-real-time State of Charge (SOC) estimation, we restricted the input sensor data history to the ten most recent observations, ensuring a balanced evaluation across methods without sacrificing generality.

In the deep neural network architecture, we employ Bidirectional Gated Recurrent Unit (BiGRU) modules as feature extractors. GRUs are well-suited for tasks involving sequential information as they efficiently capture temporal dependencies while maintaining a simpler and more streamlined architecture compared to Long Short-Term Memory (LSTM) networks. Moreover, initial experiments conducted as part of our model development phase demonstrated that GRUs outperformed LSTMs in terms of both prediction accuracy and training efficiency. In addition, (Ye & Yu, 2021) demonstrated the efficiency of BiGRU for battery state-of-health

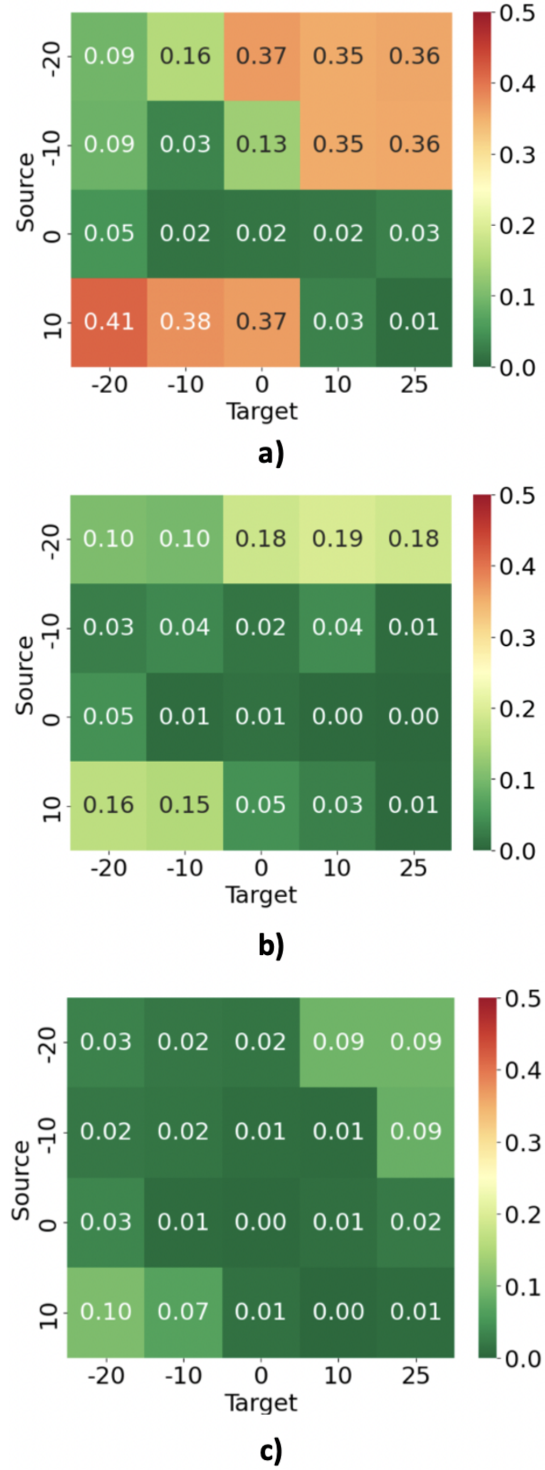

Figure 3. Heatmap of Target Mean Squared Error (MSE) for Different Domain Adaptation Methods under Different Source and Target Temperatures (°C). **a)** No TL, **b)** CORAL, and **c)** DARE-GRAM.

prediction. We run an initial set of experiments to determine the best hyper-parameters to be used in the deep learning

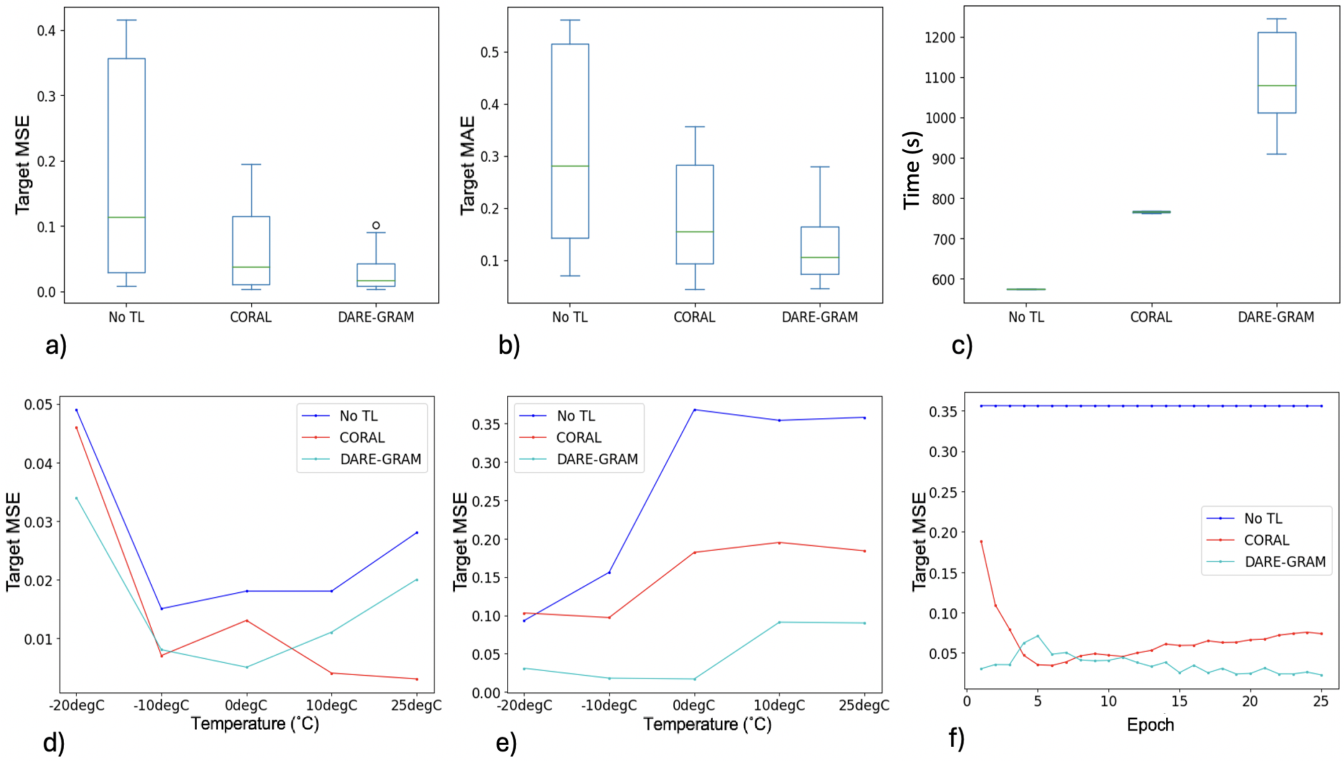

Figure 4. Comparison of Domain Adaptation Methods in State-of-Charge (SOC) Estimation. (a) Target MSE, (b) Target MAE, (c) Training Time (s), (d) Target MSE for Different Temperatures of the Target Battery when the Source Battery is Panasonic in 0°C, (e) Target MSE for Different Temperatures of the Target Battery when the Source Battery is Panasonic in -20°C , and (f) Target MSE Over Training Epochs.

model. The architecture of the feature extractors comprises five layers, each containing 200 hidden units, with a fully-connected (FC) layer consisting of 400 neurons. Additionally, L2 regularization and dropout techniques are applied to enhance the model's generalization and robustness. The number of training epochs is set to 25 for all experiments, with Mean Squared Error (MSE) serving as the loss function for the SOC prediction module.

In addition to utilizing the DARE-GRAM method, we also conduct experiments using the CORAL technique, a well-established classification-based domain adaptation approach, for performance comparison purposes. Furthermore, we perform experiments without any domain adaptation, denoted as the "No TL" model. In "No TL" model experiments, the training process excludes the utilization of target data, with the testing set of target data reserved solely for evaluating the performance of the trained model on the source data. This article utilizes mean-square error (MSE) and mean absolute error (MAE) as the performance evaluation metrics.

4. Results and Discussion

We conduct a thorough analysis of cross-battery state-of-charge (SOC) estimation, comparing the performance of regression-based and classification-based domain adaptation methods. We present the results of our experiments, focusing on the SOC estimation achieved by the BiGRU network with different domain adaptation methods.

Table 1 and Figure 3 summarize the SOC estimation outcomes. In each experiment, the Panasonic battery serves as the source domain, while the LG battery serves as the target domain. While no single domain adaptation method outperforms all others across every experiment, the DARE-GRAM method consistently demonstrates superior performance. Out of the 20 transfer learning tasks conducted, DARE-GRAM outperforms other methods in 15 tasks. Figures 4a,b illustrate box plots for the Mean Squared Error (MSE) and Mean Absolute Error (MAE) values across all tasks for different domain adaptation methods, further highlighting the superiority of the DARE-GRAM approach.

However, it is worth noting that despite its superior performance, the DARE-GRAM method demands more training time. As depicted in Figure 4c, the average training time of the model for DARE-GRAM method is approximately 40% longer compared to other methods. This disparity in computational costs can be attributed to the computation of the domain adaptation loss function. While DARE-GRAM yields

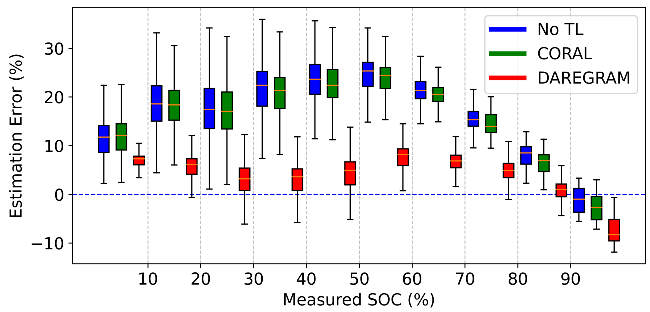

Figure 5. Comparison of Domain Adaptation Methods in SOC Estimation for Panasonic Battery at 10°C to LG Battery at 10°C Task.

impressive results, its computational overhead may pose practical considerations in certain contexts.

While the DARE-GRAM method demands a relatively longer training time over a fixed number of epochs, it exhibits a notably faster convergence, requiring significantly fewer training epochs to reach a stable state. Figure 4f shows the MSE of the target domain for different domain adaptation methods and the ”No TL” model over the training epochs for one transfer task (Panasonic -10°C to LG -10°C). This plot shows that with only one epoch, SOC estimations of the target domain for the DARE-GRAM model are significantly more accurate than other methods.

Figure 4d,e shows the results of two different temperatures of the source battery. In each plot, the MSE values of different domain adaptation methods and the ”No TL” model are depicted over different temperatures of the target battery. These two plots indicate that cross-battery SOC estimation using the measurements of the source battery under -20°C temperature is significantly more challenging than 0°C. Another important finding is that as the difference between the temperatures of the source and target domains increases, the transfer learning task becomes more rigorous.

Figure 5 illustrates the SOC estimation using different domain adaptation methods for a specific task (Panasonic 10°C to LG 10°C). While the performance of the CORAL method closely resembles that of the ”No TL” model, the DARE-GRAM method yields more accurate SOC estimations. DARE-GRAM estimates are somewhat inferior to the other methods when the battery is at full SOC.

The results reveal that for certain transfer tasks, such as Panasonic at 0°C to LG -10°C, even the ”No TL” model achieves satisfactory performance. This suggests that at under certain settings, the model trained solely on the source data can effectively estimate the state-of-charge (SOC) for the target data without the utilization of any domain adaptation or transfer learning methods in general.

5. Conclusion

In this work, we introduced a regression-based unsupervised domain adaptation method, DARE-GRAM, for SOC estimation. Through a series of experiments, we assessed the performance and effectiveness of DARE-GRAM in cross-battery SOC estimation, comparing its results with those obtained using the classification-based UDA method, CORAL. Our findings consistently demonstrate the superiority of the DARE-GRAM method in achieving accurate SOC estimation. DARE-GRAM consistently outperformed CORAL, showcasing its robustness and adaptability across various battery domains. Moreover, DARE-GRAM exhibited the ability to prevent negative transfer, ensuring that knowledge transfer did not compromise SOC estimation performance. Furthermore, our results underscored the influence of ambient temperature on model transferability. When the ambient temperatures of both the source and target batteries were similar or closely aligned, the transferability of the model was notably enhanced, leading to improved SOC estimation accuracy. Overall, our study highlights the effectiveness of DARE-GRAM as a powerful tool for enhancing SOC estimation in diverse battery management scenarios, offering valuable insights for future research in the field.

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