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Estimating battery state-of-charge with a few target training data by meta-learning

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HIGHLIGHTS

- A meta-learning method for battery state-of-charge estimation is proposed.
- The method reduces the target battery data required to train a deep-learning model.
- Meta-learning does not require the similarity of pre-trained and target batteries.
- Meta-learning can reduce the number of gradient steps in the fine-tuning process.
- Its performance is verified by battery test data of standard driving cycles.

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ABSTRACT

This study proposes a meta-learning battery state-of-charge (SOC) estimation approach to reduce the amount of target battery data required for training a Li-ion battery SOC estimation by applying deep-learning. The proposed approach reduces the training data required for the target battery by improving the pre-training performance. Multiple other batteries are used as pre-training data to allow generalization to the target battery. The performance of meta-learning SOC estimation is compared with that of transfer learning using one battery data for pre-training. The meta-learning performance does not depend on the similarity between the pre-training data and target battery data. The proposed meta-learning SOC estimation accuracy is verified based on battery test data from various driving cycles (US06, urban dynamometer driving schedule (UDDS), and LA92), to reflect actual electric vehicle driving patterns. Using only a small amount of target battery data and nine gradient steps, the proposed meta-learning SOC estimation algorithm achieves a mean squared error (MSE) of 0.0176% and a mean absolute error (MAE) of 1.0075%. These results show that the proposed method can adapt more quickly than transfer learning (with SOC estimation errors of 3.1378% in terms of the MSE and 15.1327% in terms of the MAE under the same conditions).

1. Introduction

This paper presents a Li-ion battery state-of-charge (SOC) estimation method that uses meta-learning (a deep-learning method). A battery SOC estimation method that uses deep-learning can achieve a higher SOC estimation accuracy than battery-modeling-based SOC estimations. In addition, a deep-learning SOC estimation model can be easily implemented without the need for prior theoretical knowledge of a battery equivalent model [1]. Therefore, it does not require battery-parameter extraction experiments and precise battery modeling, whereas a battery modeling method requires these tasks. Therefore, a deep-learning SOC estimation is an effective and easy-to-apply method for battery management systems [2].

In the previous battery SOC estimation studies, various SOC estimation algorithms such as coulomb counting [3,4], open circuit voltage (OCV) method [5–7], Kalman filter (KF) algorithm [8,9], and extended KF (EKF) algorithm [10–12] have been proposed. A coulomb counting method [3,4] is a method of calculating the remaining capacity by accumulating the current charged and discharged in the battery. When the current is integrated, the measurement error of the current sensor is also accumulated, and the longer the estimation time, the larger the error in the SOC estimation [13]. An OCV method [5–7] estimates SOC

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through the relationship between OCV and SOC. This method allows quite accurate SOC estimation for measuring the OCV of the battery after a long stabilization time. It can also estimate battery SOC with reasonable accuracy during periods of low current flow with the information of the battery polarization characteristics. However, this OCV approach may not be suitable for real-time battery SOC estimation [14]. A KF algorithm [8] is an algorithm that can incrementally modify SOC estimation results through iteration. Although a KF algorithm [8] is a widely used adaptive filter for linear models, it is not suitable for non-linear models such as lithium-ion batteries [15]. An EKF algorithm [10–12] uses linear Taylor series expansions and partial derivatives to linearize non-linear models. However, when a non-linear model is in a highly non-linear condition, a large error occurs in an SOC estimation [16]. Therefore, data-driven deep-learning SOC estimation algorithms have been proposed to overcome these problems of previous studies [1,2].

However, a deep-learning SOC estimation algorithm requires a large amount of battery charge/discharge data [17]. This is a major disadvantage because obtaining such a large amount of battery charge/discharge data takes a long time and is expensive, but remains an essential prerequisite for training a deep-learning model [18]. If the type of the trained battery is different from that of the target battery, the deep-learning model training should be restarted, after collecting the training data of the target battery [19,20]. This problem may represent a significant disadvantage, in that a considerable amount of time and expense are required to develop the battery management systems (BMSs) for electric vehicles of diverse and various types.

Diverse deep-learning SOC estimation algorithms including deep neural network (DNN) [2,21,22], long short-term memory (LSTM) [23–26], and gated recurrent unit (GRU) [1,27] have been presented in the literature. For the training data of the target battery, a DNN model [2,21,22] requires numerous battery charge/discharge data from electric vehicle standard driving cycles such as highway fuel economy test (HWFET), LA92, urban dynamometer driving schedule (UDDS), and US06 to estimate the target battery SOC. In Ref. [22], a DNN model was used to estimate the SOC of sodium-ion batteries different from conventional lithium-ion batteries. In Ref. [22], charge/discharge data were constructed by changing the C rate from 0.05C to 2C-rate to compose the training data of the target battery. Therefore, if a new target battery has different chemical structures or specifications from an existing lithium-ion battery, training data must also be newly constructed to learn the new target battery although previous training data from the existing lithium-ion battery have been retained.

An LSTM model [23–26] has excellent performance in time-dependent estimation tasks such as a battery SOC estimation. However, as in the previous DNN model study, a large amount of training data is required for an LSTM model to have accurate SOC estimation performance for the target battery. A GRU model [1,27] also has excellent performance in estimating the battery SOC. Compared to the LSTM model, the number of parameters modified by training is small in the GRU model although a large amount of training data is required for an accurate SOC estimation.

In order to solve such training-data-acquisition problems in deep-learning-model training, a transfer-learning SOC estimation approach [28] has been proposed. Transfer learning is a method for reducing the amount of training data by applying a pre-trained deep-learning model to another model, instead of training the model from scratch. Based on pre-trained battery data, transfer learning can train the SOC estimation for a new target battery [29]. The reuse of pre-trained battery data in the new target battery training saves experimental time and expense to obtain the target battery training data.

However, the performance of transfer learning depends highly on the similarity of the previously trained battery characteristics with those of the target battery [30]. Transfer learning shares pre-trained model parameters to facilitate better training of the target battery model. Therefore, the SOC estimation performance of the target model depends on the similarity of the pre-trained battery data with the target battery data, because the weights of the pre-trained model are applied to the target model [31]. However, it is very difficult to determine the similarity of battery dynamic characteristics, as they vary according to the electrical and chemical characteristics of the pre-trained battery and target battery. Because of this problem, applying transfer-learning SOC estimation to a new battery with a pre-trained model may not obtain accurate results in the early development stage of a BMS.

This paper presents a meta-learning SOC estimation method for achieving high performance with a small amount of target battery training data by pre-training multiple types of battery data. Similar to transfer learning, meta-learning has been applied in the image processing field [32] to solve problems regarding insufficient training data. The transfer-learning SOC estimation method reuses the deep-learning model parameters trained with only one type of battery. Hence, general deep-learning and transfer learning may not be effective for estimating a battery SOC by using battery data acquired in a previous BMS development for a new BMS development, unless the target battery is the same as the previously developed BMS battery. In contrast, meta-learning SOC estimation optimizes the pre-trained model parameters to estimate the target battery SOC, by utilizing only a small number of target battery training samples. In other words, meta-learning SOC estimation can use other previously acquired battery data and the target battery data to develop the new BMS. Therefore, meta-learning SOC estimation can save the time and economical expenses ordinarily required to acquire battery training data. Specifically, meta-learning can effectively solve the problem of repeating the new BMS development process caused by a fast new EV launch cycle. In other words, meta-learning can be adapted to new battery SOC estimation with the existing BMS hardware, although the specification of Li-ion batteries is changed.

The specific contributions of this study are described as follows.

1) The proposed meta-learning SOC estimation can reduce the amount of target battery data required for its training by reusing battery charge/discharge data previously obtained from other BMS development tasks. Therefore, it can reduce the BMS development time and expense; this is important because it is difficult to obtain long-term battery cycle data for a target battery in the early stages of BMS development.
2) The performance of a transfer-learning SOC estimation is mainly determined by the similarity between the pre-trained battery data and the target battery data, because transfer learning is based on pre-training data from a single type of battery. In contrast, the proposed meta-learning method can achieve stable and effective SOC estimation performance by optimizing the pre-trained model parameters with a small amount of target battery training data.
3) The number of gradient steps in the fine-tuning process is related with the development time because the fine-tuning should be repeatedly performed until satisfying the required SOC estimation accuracy. The proposed meta-learning can reduce the number of gradient steps in the fine-tuning process for estimating the target battery SOC to reduce the development time.

The remainder of this paper is structured as follows. The proposed meta-learning SOC estimation method is described in Section 2. Section 3 describes the configuration and information of the actual battery dataset applied in the proposed meta-learning SOC estimation. To verify the proposed meta-learning SOC estimation, experimental results are presented in Section 4. Finally, conclusions are provided in Section 5.

2. Proposed methodology of meta-learning for fast adaptation to battery state-of-charge (SOC) estimation

This section describes the proposed meta-learning SOC estimation method, which uses other battery data to pre-train the target battery for faster adaptation than that with other deep-learning SOC estimation methods. The proposed method is effective when the target battery training data are insufficient, specifically in the early stages of BMS development. Fig. 1 illustrates the training process for a meta-learning SOC estimation model, compared with a general deep-learning model with no pre-training and a transfer learning model.

Fig. 1(a) illustrates a battery SOC estimation training process using a general deep-learning model with no pre-training. As shown in Fig. 1(a), the input/output data of general deep-learning with no pre-training comprise the charge/discharge data of the batteries, $i(i = 1, 2, \ldots, N)$, to be estimated. In other words, the input data, $X_i(i = 1, 2, \ldots, N)$, comprise each battery's state information, such as its voltage ($V_i(i = 1,2,\ldots,N)$), current ($I_i(i = 1,2,\ldots,N)$), and temperature ($T_i(i = 1,2,\ldots,N)$), and the output data, $Y_i(i = 1, 2, \ldots, N)$, consist of their corresponding actual SOC values. To estimate the SOCs for N number of different batteries, a general deep-learning SOC estimation requires N different deep-learning models, $\mathrm{m}_i(i = 1,2,\ldots,N)$. For each deep-learning initial model (m), the SOC estimated value, $Y_{est\_i}(i = 1, 2, \ldots, N)$, can be calculated by using the input value, X_i, and the initial value of the model parameter, $\varnothing$. A loss function ($\mathscr{L}_i(i = 1,2,\ldots,N)$) that compares Y_i with Y_{est_i} can be used to update the deep-learning model parameter, $\varnothing$, to $\dot{\varnothing}_i(i = 1,2,\ldots,N)$, such that Y_i is close to Y_{est_i}. If there are enough charge/discharge data of battery i to be estimated, $\varnothing$ can be updated by deep-learning model m_i such that Y_{est_i} is close to Y_i.

In contrast, the transfer-learning SOC estimation method depicted in Fig. 1(b) pre-trains the charge/discharge data of a battery similar to the target battery to build model m_1. To estimate the target battery SOC, transfer learning does not use the initial parameter, $\varnothing$, of model m_1; rather, it uses the pre-trained model parameter, $\dot{\varnothing}_1$, as the initial parameter of model $\mathrm{m}_{Transfer}$. Although the general deep-learning SOC estimate, Y_{est_1}, is derived by calculating the initial parameter, $\varnothing$, the transfer-learning SOC estimate, Y_{est_T}, is derived by using the pre-trained model parameter, $\dot{\varnothing}_1$. Therefore, the update process of the deep-learning model parameter, $\dot{\varnothing}_{target}$, by using the loss function, $\mathscr{L}_T$, can be reduced in transfer learning than in general deep-learning. However, the amount of reduction in the update process to $\dot{\varnothing}_{target}$ is determined by the similarity between $\dot{\varnothing}_{target}$ and the pre-trained model parameter, $\dot{\varnothing}_1$.

In contrast, the meta-learning SOC estimation pre-trains various types of battery data except the target battery data, to avoid the pre-training performance being determined by the degree of similarity between parameter $\dot{\varnothing}_1$ of a single pre-training model and the target model parameter, $\dot{\varnothing}_{target}$. Fig. 1(c) presents the pre-training and target training processes of the meta-learning SOC estimation. Unlike the pre-training process of transfer learning described earlier, the model parameters, $\dot{\varnothing}_i(i = 1,2,\ldots,N)$, of the deep-learning models, $\mathrm{m}_i(i = 1, 2, \ldots, N)$, in meta-learning are pre-trained with the data of various types of batteries, $i(i = 1,2,\ldots,N)$. Meta-learning is the pre-training process for determining parameter $\dot{\theta}_{Meta}$ that can quickly adapt to the model parameters, $\dot{\varnothing}_i$, of the deep-learning models, m_i. $\dot{\theta}_{Meta}$ obtained through meta-learning is used as an initial parameter of the target battery SOC training model, M_{meta}. The calculation process for updating $\dot{\theta}_{Meta}$ to model parameter $\dot{\varnothing}_{target}$ by using the loss function $\mathscr{L}_M$ is reduced compared with the process in which the initial parameter, $\varnothing$ is updated to $\dot{\varnothing}_{target}$. Moreover, compared with transfer learning, where the pre-training performance is determined by the similarity between $\dot{\varnothing}_1$ and $\dot{\varnothing}_{target}$, meta-learning can further reduce the update process for the deep-learning model parameter, $\dot{\varnothing}_{target}$, because model parameter $\dot{\theta}_{Meta}$ in meta-learning can adapt to various model parameters, $\dot{\varnothing}_i$.

2.1. Meta-learning pre-learning method

Before the target battery SOC is estimated, various batteries, except for the target battery, are pre-trained by using generally optimized meta-learning [32], which is applicable to a deep-learning model trained with a gradient descent. Algorithm 1 describes the overall pre-training procedure of the meta-learning model, M_{meta}, for battery SOC estimation. First, the battery charge/discharge data, including the voltage, current, temperature, and SOC information, of the various batteries ($i(i = 1,2,\ldots,N)$) except for the target battery are defined as the training dataset, $D_i^{meta-train}$, for meta-learning. Then, $D_i^{meta-train}$ is divided into $D_i^{pre-train}$ for pre-training and D_i^{test} for testing. Meta-learning with $D_i^{pre-train}$ is utilized to update parameter $\dot{\varnothing}_i$ by parameter θ_{Meta} of deep-learning model M_{meta} as follows:

$$\dot{\varnothing}_i = \theta_{Meta} - \alpha \nabla_{\theta_{Meta}} \mathscr{L}_i\left(\theta_{Meta}, D_i^{pre-train}\right), \tag{1}$$

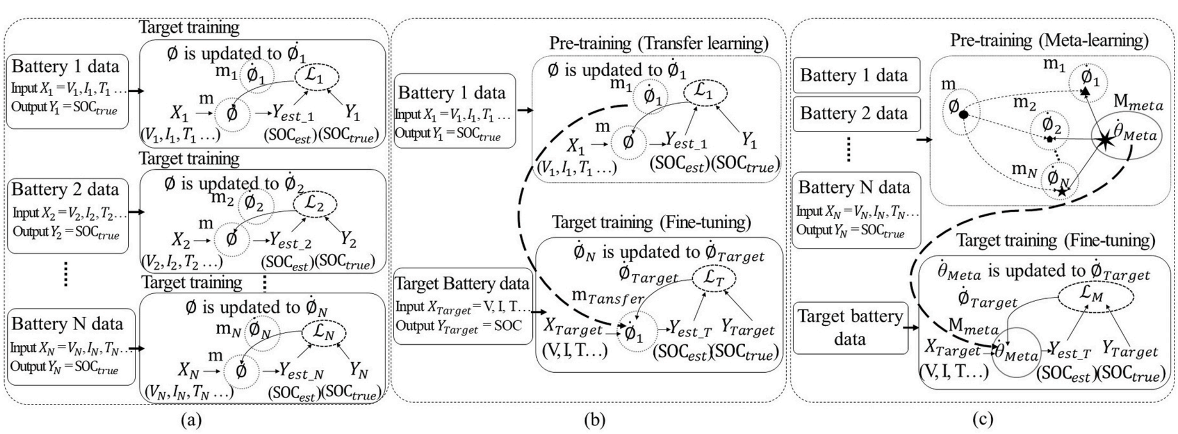

Fig. 1. Deep-learning-model training methods for battery state-of-charge (SOC) estimation: (a) general deep-learning with no pre-training, (b) transfer learning, and (c) meta-learning.

Algorithm 1. Meta-learning

Algorithm 1. Meta-learning

Define : meta-learning training data, $D_i^{meta-train}$, with information of various batteries, $i(i = 1, 2, \dots, N)$, except the target battery

1: divide $D_i^{meta-train}$ $into$ $D_i^{pre-train}$ and D_i^{test}

2: for all $D_i^{meta-train}$ $(i.e., D_i^{pre-train}, D_i^{test})$ do

3: $\dot{\phi}_i$ is calculated by using θ_{Meta} and $D_i^{pre-train}$

$\dot{\phi}_1 = \theta_{Meta} - \alpha\nabla_{\theta_{Meta}}\mathcal{L}(\theta_{Meta}, D_1^{pre-train})$,

$\dot{\phi}_2 = \theta_{Meta} - \alpha\nabla_{\theta_{Meta}}\mathcal{L}(\theta_{Meta}, D_2^{pre-train})$,

$\dots$, $\dot{\phi}_N = \theta_{Meta} - \alpha\nabla_{\theta_{Meta}}\mathcal{L}(\theta_{Meta}, D_N^{pre-train})$

4: θ_{Meta} is updated to $\dot{\theta}_{Meta}$ by $\dot{\phi}_i$ and D_i^{test}

$$\dot{\theta}_{Meta} = \theta_{Meta} - \beta\nabla_\theta\sum_i \mathcal{L}_i(\dot{\phi}_i, D_i^{test})$$

5: end

Where α is a weighting factor that indicates a learning rate by which $\varnothing_i$ will be shifted in the gradient direction.

Parameter θ_{Meta} is initially defined as a random value. Meta-learning is employed to pre-train θ_{Meta} for minimizing the loss function, $\mathscr{L}_i$, used to update $\dot{\varnothing}_i$. In other words, θ_{Meta} is updated to satisfy the following:

$$\begin{aligned} min_{\dot{\theta}_{Meta}} &= \sum_i \mathscr{L}_i\left(\theta_{Meta}, D_i^{pre-train}\right) \\ &= \sum_i \mathscr{L}_i\left(\theta_{Meta} - \alpha\nabla_{\theta_{Meta}}\mathscr{L}\left(\theta_{Meta}, D_i^{pre-train}\right)\right), \end{aligned} \tag{2}$$

where $\mathscr{L}_i$ denotes all loss functions required for updating $\dot{\varnothing}_i$. Then, as described in (3), θ_{Meta} is finally updated to $\dot{\theta}_{Meta}$, in which the loss function of the model parameter, $\dot{\varnothing}_i$, has the minimum value, by using the test dataset, D_i^{test}.

$$\dot{\theta}_{Meta} = \theta_{Meta} - \beta\nabla_\theta\sum_i \mathscr{L}_i\left(\dot{\varnothing}_i, D_i^{test}\right), \tag{3}$$

where β is the step size to update θ_{Meta} with $\dot{\theta}_{Meta}$.

2.2. *Target battery SOC estimation of a pre-trained deep-learning model through meta-learning*

Fig. 2 shows the process of the target battery SOC estimation using meta-learning based on pre-trained data from multiple batteries except for the target battery. To conduct meta-learning with deep-learning model M_{meta}, training dataset $D_i^{meta-train}$ of various batteries except the target battery is divided into a pre-training dataset, $D_i^{pre-train}$, and a test dataset, D_i^{test}, as depicted in Fig. 2. Meta-learning is used to construct model M_{meta} that can be quickly adapted to various types of battery SOC estimations with $\dot{\theta}_{Meta}$ obtained from the pre-training.

Once the pre-training is completed by the meta-learning, model M_{meta} is fine-tuned by using the target training data, D_{target}, so that it can estimate the target battery SOC. D_{target} is composed of the charge/discharge data of the target battery. The input data for the target training (fine-tuning) consist of the target battery's voltage, current, and temperature, and its output data comprise the corresponding actual SOC value of the target battery. The model parameter, $\dot{\theta}_{Meta}$, of model M_{meta} is fine-tuned to $\dot{\varnothing}_{target}$ through D_{target} as follows:

$$\dot{\varnothing}_{target} = \dot{\theta}_{Meta} - \gamma\nabla_\theta\mathscr{L}_f\left(\dot{\theta}_{Meta}, D_{target}\right) \tag{4}$$

where γ is the step size applied during the fine-tuning process. The loss function, $\mathscr{L}_f$, used in the fine-tuning is calculated based on the mean squared error (MSE) between the estimated SOC values, $X_i(i = 1, 2, \dots, N)$, and the actual SOC values, $Y_i(i = 1, 2, \dots, N)$, as described in (5). The

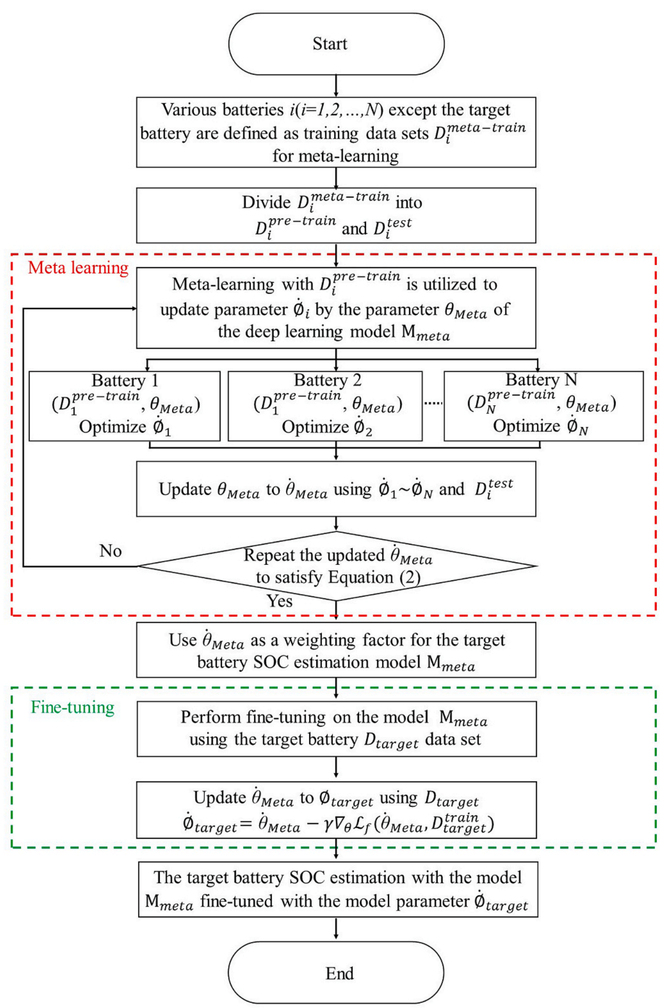

Fig. 2. Pre-training through meta-learning and fine-tuning process for estimating the target battery SOC.

estimated SOC values, X_i, can be calculated by using $\dot{\varnothing}_{target}$ and the input data of D_{target}, and the actual SOC values, Y_i, are the output data of D_{target}.

$$\mathscr{L}_f(\mathrm{M}_{meta}) = \frac{1}{2}\sum_i (X_i - Y_i)^2 \tag{5}$$

Once the fine-tuning process is completed, the target battery SOC can be estimated by using the fine-tuned model, M_{meta}. To verify the estimated accuracy of model M_{meta}, error measurement metrics, namely, the MSE, mean absolute error (MAE), and absolute error are used in this study, as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{K=1}^{n}\left(SOC_{est,K} - SOC_{true,K}\right)^2, \tag{6}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{K=1}^{n}\left(\left|SOC_{est,K} - SOC_{true,K}\right|\right), \tag{7}$$

$$\text{Absolute Error} = \left|SOC_{est,K} - SOC_{true,K}\right|, \tag{8}$$

where $SOC_{est,K}$ is the estimated SOC value, $SOC_{true,K}$ is the actual SOC value, and n is the number of test samples.

3. Battery specifications and data set

To train the meta-learning model for the experiment, Samsung (INR 18650-20R) Li-ion battery data [33–35], obtained by the Center for Advanced Life Cycle Engineering Battery Research Group, were used in this study. Panasonic (NCR18650PF) [17,27,36], Samsung (IN21700-30T) [37], and LG (18650HG2) [38] Li-ion battery data, obtained by McMaster University in Hamilton, Ontario, Canada, were also used. As with the previous literature [1,2,17,25,27–30,33–38], all Li-ion battery data used in this study were measured in a single cell unit. As listed in Table 1, the Li-ion batteries used in the experiment had different specifications, such as charge/discharge capacities, voltages, and current dynamic characteristics. As described in Table 1, the battery charge/discharge data used in the experiment were obtained by applying different actual road driving cycles. Specifically, the driving cycles applied for the investigated battery data included highway driving conditions (HWFET), city driving conditions (US06 and UDDS), and hybrid highway-city driving conditions (the Beijing Dynamic Stress Test (BJDST)). In addition, the battery charge/discharge data obtained by the LA92 driving cycle were used to reflect radical driving patterns and dynamic battery current changes. All the battery charge/discharge data used in this study were measured and recorded every second. In other words, one data point of battery charge/discharge data included various measured battery signals, such as voltage, current, and temperature, recorded every 1-s interval.

Fig. 3 depicts the charge/discharge voltage and current data during the US06 driving cycle operation for all batteries used in the experiment at 25 °C. As shown in Fig. 3, the dynamic voltage and current characteristics of each battery are different, even for the same US06 driving cycle. The charge/discharge data used in the experiment are the same instantaneous battery voltage and current values that are used as input values for the deep-learning model. Based on Coulomb counting, the true SOC values in the experiment are calculated as follows:

$$SOC_t = SOC_{t-1} + \int_{t-1}^{t} \frac{I_t}{Q_{initial}}\,dt, \tag{9}$$

where SOC_t and SOC_{t-1} denote the true SOC values at time t and t-1, respectively; $Q_{initial}$ denotes the nominal capacity of the battery, in Ah; and I_t is the battery charge/discharge current at time *t*.

Fig. 4 summarizes the training data amount of the target battery used in the fine-tuning process in meta-learning and other deep-learning SOC estimation algorithms [1,2,25,28–30]. One training data point in the *y*-axis of Fig. 4 represents battery measurement data in the 1-s interval. Transfer-learning researches [28–30] have used at least 4 cycles of actual road driving cycles (i.e., at least 32,000 data points) as the target battery training data. In Ref. [2], a DNN model was trained with up to seven complete discharge datasets (i.e., at least 37,000 data points). In the study of [25], an LSTM model was trained with three actual road driving cycles' data (i.e., at least 24,000 data points). A GRU model [1] was trained with one actual road driving cycle (i.e., at least 8300 data points). In other words, the training processes of conventional deep-learning models require at least one or more cycles of charge/discharge data of the target battery. On the other hand, in order to verify that meta-learning can sufficiently estimate the target battery SOC even with a small amount of training data, this study used 96 data points (i.e., 3 data points extracted every 100-s) for the meta-learning fine-tuning process.

4. Experimental results

This section presents the experimental results of meta-learning SOC estimation to verify its estimation performance compared with that of transfer-learning SOC estimation (a pre-trained deep-learning SOC estimation method). The pre-training effect on the battery SOC estimation was verified by comparison with the training performance of other deep-learning models with no pre-training (i.e., DNN, LSTM, and GRU). The investigated pre-training-based deep-learning models, including meta-learning and transfer learning, used a DNN model. The DNN structure of this study was composed of 64 neurons and four hidden layers, based on the results of a study [21] on the battery SOC estimation performance by the DNN structure. The deep-learning models, including LSTM and GRU, were composed of a single LSTM layer with 300 neurons and a single GRU layer with 150 neurons based on the results of the battery SOC deep-learning estimation study [1,25]. In addition, a rectified linear unit activation function and an Adam optimizer were used in this study. Error measurement metrics including the MSE and MAE were used to evaluate the SOC estimation performance of the meta-learning, transfer learning, and general deep-learning methods with no pre-training. The investigated SOC estimation models were trained by using NVIDIA 2080Ti graphical processing units with a TensorFlow deep-learning framework.

4.1. *Meta-learning SOC estimation from a small amount of target battery data*

A meta-learning SOC estimation model pre-trained by multiple batteries (except the target battery) can predict the target battery SOC by fine-tuning a small amount of target battery data in a few gradient steps. In order to examine the meta-learning SOC estimation performance, this study compared the pre-training performances of meta-learning and

Table 1
Battery specifications.

Battery Model	Cut-off Voltage (V)	Maximum Current (A)	Nominal Capacity (Ah)	Driving Cycle (Total Number of Data Points)
Samsung (IN21700–30T)	2.5/4.2	35	3.0	US06(13,908), HWFET(26,030)
Samsung (INR18650–20R)	2.4/4.2	22	2.0	US06(11,899), BJDST(12,437)
Panasonic (NCR18650PF)	2.5/4.2	10	2.9	US06(48,062), LA92(137,875)
LG (18650HG2)	2.0/4.2	20	3.0	US06(4015), LA92(9475), UDDS(15,964)

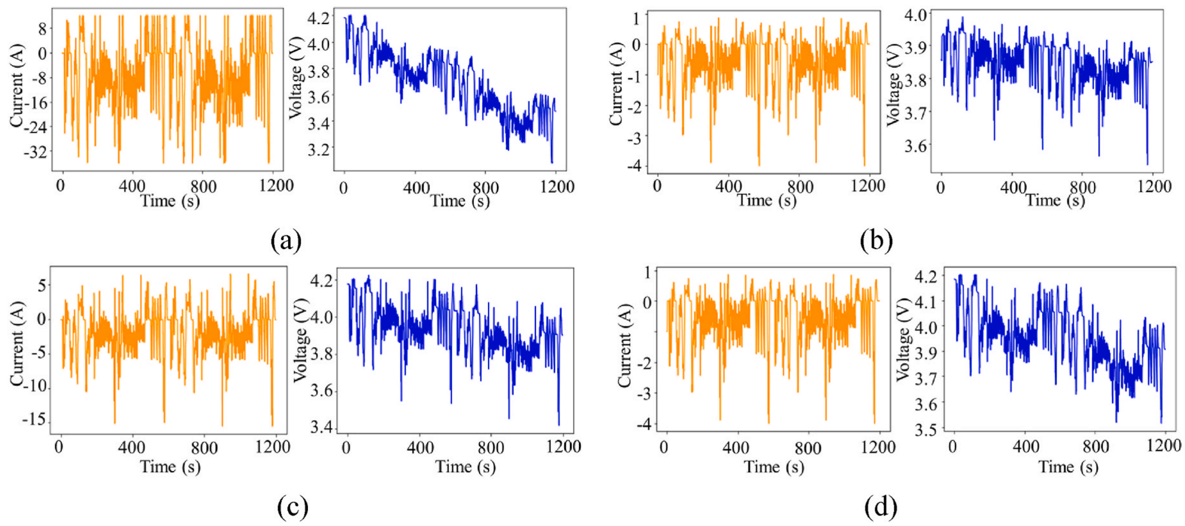

Fig. 3. US06 driving cycle battery data: (a) Samsung IN21700-30T, (b) Samsung INR18650-20R, (c) Panasonic NCR18650PF, and (d) LG 18650HG2.

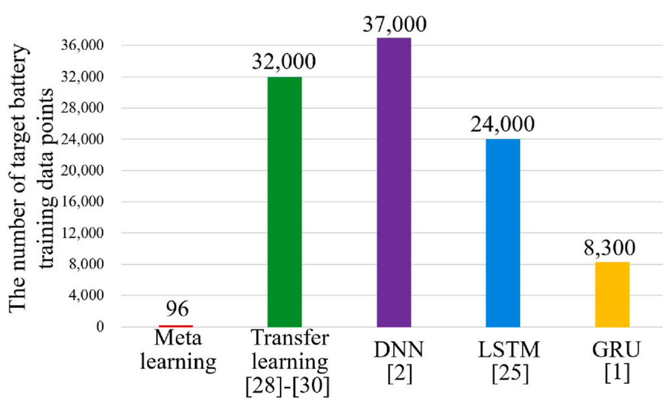

Fig. 4. The number of target battery training (i.e., fine-tuning) data points for SOC estimations.

transfer learning according to the number of gradient steps. These pre-trained SOC estimation models constructed with DNNs were fine-tuned using a small amount of target battery data. Fig. 5 depicts the SOC estimation performance in case of pre-training, based on Panasonic (NCR18650PF) and Samsung (IN21700-30T and INR18650-20R) battery data. For the target battery data, the US06 driving cycle LG (18650HG2) data were used in the experiment. In order to verify their SOC estimation performance in a small amount of target battery data, only three data points in every 100-s interval of the target battery data (as depicted in Fig. 5(a) and (b)) were applied to fine-tune the pre-trained models.

Fig. 5(a) illustrates the SOC estimation performance of the meta-learning model with respect to the change in the number of gradient steps. As depicted in Fig. 5(a), the absolute error of the meta-learning SOC estimation is reduced to approximately 30% when its pre-trained DNN model from meta-learning is fine-tuned with a small amount of the target battery data in one gradient step. In addition, the meta-learning nearly estimates the true SOC values in just nine gradient steps, as shown in Fig. 5(a). In contrast, as depicted in Fig. 5(b), transfer learning had substantial absolute errors in the SOC estimation, even though the number of gradient steps in the fine-tuning increased. In addition, transfer learning showed an absolute error of approximately 55% in the SOC estimation without any fine-tuning (with zero gradient steps); this is higher than the value for meta-learning in the same gradient step. In addition, although the meta-learning nearly estimates the true SOC values in only nine gradient steps of fine-tuning, the transfer learning still has large absolute errors in the SOC estimation, even after the nine steps are applied. These results show that meta-learning can accurately estimate the target battery SOC with only a small number of target battery data, and in a small number of gradient steps.

Fig. 5(c) and (d) respectively show the target battery SOC estimation error results in terms of the MSE and MAE, depending on the number of gradient steps in both pre-trained DNN models (meta-learning and transfer learning) and a DNN model with no pre-training. The meta-learning shows a tendency to dramatically decrease the MSE and MAE in just one gradient step. These results indicate that a DNN model with meta-learning quickly adapts to the target battery SOC estimation. In addition, the meta-learning estimation errors reduce to less than 1% in the MSE and MAE after applying the nine gradient steps of the fine-tuning. Based on these results, the meta-learning in subsequent experiments was performed by fine-tuning with nine gradient steps. In contrast, transfer learning, in which the SOC estimation errors of the MSE and MAE gradually decrease, is not trained properly compared with meta-learning. Moreover, the SOC estimation errors in DNN models with no pre-training tend to decrease more slowly because their models are not pre-trained.

4.2. SOC estimation with US06 driving cycle

This section presents the target battery SOC estimation performance results of the DNN model pre-trained with meta-learning for the entire US06 driving cycle, i.e., an actual city road driving cycle. The effect of meta-learning was also evaluated by comparing its SOC estimation performance with that of other deep-learning models with no pre-training (i.e., DNN, LSTM, and GRU).

The meta-learning SOC estimation model was pre-trained using the US06 driving cycle data of the Samsung (IN21700-30T and INR18650-20R) and Panasonic (NCR18650PF) batteries. Because one transfer learning SOC estimation model can only pre-train one type of battery data, the data of three batteries (Samsung (IN21700-30T and INR18650-20R) and Panasonic (NCR18650PF)) were individually pre-trained in each transfer learning experiment. In addition, the other deep-learning models (DNN, LSTM, and GRU) were not pre-trained to evaluate SOC estimation performance.

In order to verify the effect of the fine-tuning data amount, this study evaluated the SOC estimation performance of the deep-learning models depending on the data amount used for fine-tuning. The fine-tuning was performed with nine gradient steps by applying a stochastic gradient descent optimizer. Fig. 6 illustrates the SOC estimation results of the

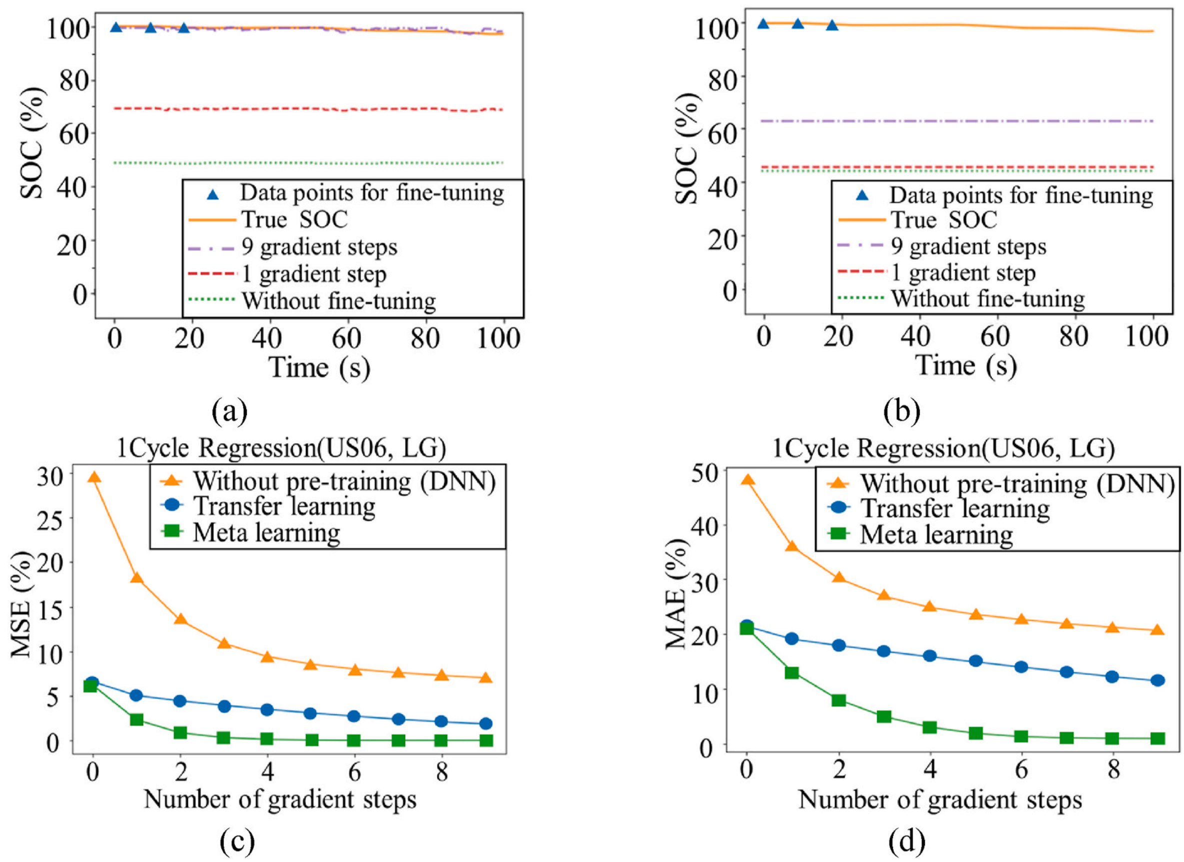

Fig. 5. Comparison of SOC estimation results according to the number of gradient steps: (a) meta-learning, (b) transfer learning, (c) mean squared error (MSE), and (d) mean absolute error (MAE).

target battery obtained by fine-tuning the deep-learning models (i.e., meta-learning, transfer-learning, DNN, LSTM, and GRU) with 8000 data measured at 1-s intervals. In addition, Fig. 7 depicts the SOC estimation results of the target battery attained by fine-tuning the deep-learning models (i.e., meta-learning, transfer-learning, DNN, LSTM, and GRU) with 96 data measured every 100-s. In order to evaluate the target battery SOC estimation performance of the investigated methods, the US06 driving cycle of the LG (18650HG2) data were used in the experiment as the target battery data.

Fig. 6 and Table 2 show the SOC estimation results of the investigated deep-learning models after fine-tuning 8000 data points of the target battery. As shown in Fig. 6(f)~(j), the absolute SOC estimation errors of meta-learning, transfer learning, LSTM, and GRU methods at each point during the entire time were less than 5%. Therefore, if there is enough target battery data to fine-tune the deep-learning models, an accurate SOC estimation is possible. However, as seen in Fig. 6(h), a DNN model requires a larger amount of target battery data for fine-tuning than other models as confirmed in Fig. 4.

SOC estimation results from a small amount of target battery data are shown in Fig. 7 and Table 3. As depicted in Fig. 7, the SOC estimation results for meta-learning show a more accurate estimation performance than those of transfer learning and general deep-learning with no pre-training (i.e., DNN, LSTM, and GRU), although meta-learning uses relatively few gradient steps (nine steps). Furthermore, as shown in Fig. 7(f), the absolute errors of the meta-learning SOC estimation at each point during the entire time are less than 5%. However, as depicted in Fig. 7(g)~(j), transfer learning and general deep-learning with no pre-training (i.e., DNN, LSTM, and GRU) have high absolute errors in the SOC estimation over the entire time. These inaccurate estimation results are caused by the fact that these methods were not yet sufficiently trained, owing to the lack of data and the small number of learning operations.

To quantitatively compare the SOC estimation errors, the MSE and MAE errors are listed in Table 3. The transfer-learning SOC estimation experiments were conducted three times by separately pre-training Samsung (IN21700-30T and INR18650-20R) and Panasonic (NCR18650PF) battery data. As listed in Table 3, transfer learning results from pre-training with Samsung (IN21700-30T) data show an MSE of 3.1378% and an MAE of 15.1327%. These relatively accurate transfer learning SOC estimation results with the Samsung (IN21700-30T) pre-trained data result from the specification similarity between the pre-trained battery and target battery. However, the meta-learning SOC estimation method can obtain more accurate results (0.0176% MSE and 1.0075% MAE) than the other investigated methods, as listed in Table 3.

4.3. SOC estimations with various driving cycles

This section presents the SOC estimation performance of the meta-learning when using various driving cycle battery data. In order to verify the accuracy of the meta-learning SOC estimation, the following experiments were conducted under the condition that pre-training data were configured with various battery types and driving cycles, and without considering the similarity between the target

Battery and pre-training batteries. Different battery charge/discharge data with several driving cycles, including the BJDST (Samsung INR18650-20R), LA92 (Panasonic NCR18650PF), and HWFET (Samsung IN21700-30T) were used for pre-training in the meta-learning experiment. The performance of meta-learning SOC estimation was evaluated by using the UDDS and LA92 driving cycle data from the LG 18650HG2 battery as the target battery data. In the experiment, the meta-learning step size β and inner learning rate α were set to 0.001 and 0.0186, respectively. The fine-tuning process (96 target battery data

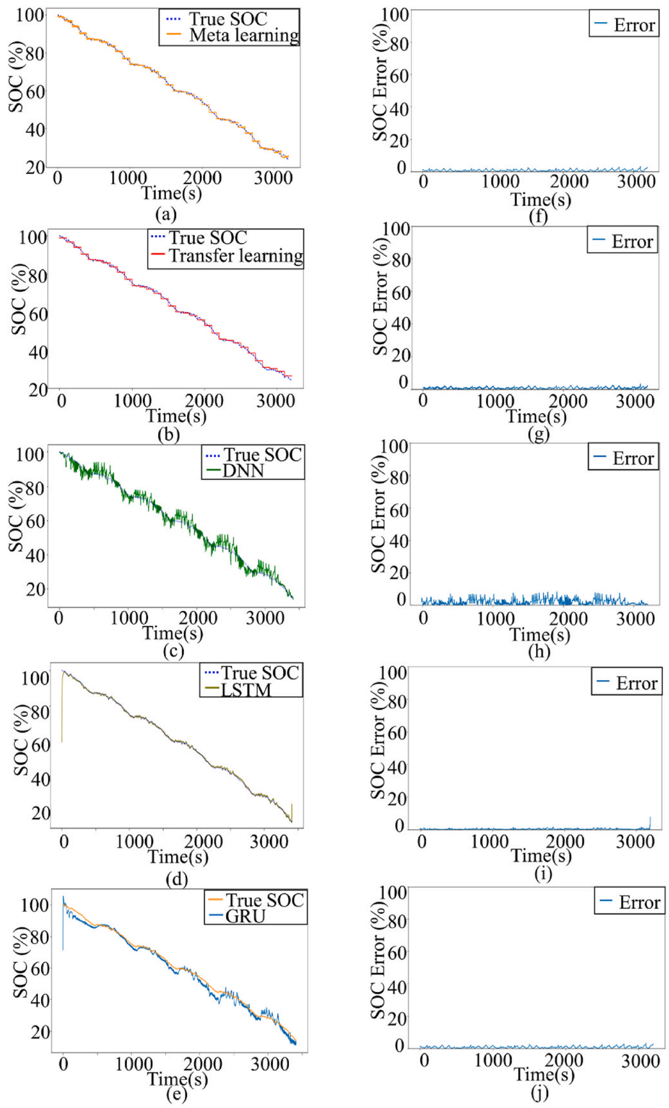

Fig. 6. SOC estimation performance evaluation at US06 Driving cycle (fine-tuned with 8000 data points): (a) meta-learning result, (b) transfer learning result by pre-training Samsung IN21700-30T, (c) DNN result, (d) LSTM result, (e) GRU result, (f) meta-learning SOC errors, (g) transfer learning SOC errors by pre-training Samsung IN21700-30T, and (h) DNN SOC errors, (i) LSTM SOC errors, (j) GRU SOC errors.

points and nine gradient steps) described in Section 4.2 was also applied in this experiment.

Fig. 8 and Table 4 show the SOC estimation results from meta-learning, transfer learning, DNN, LSTM and GRU in the UDDS driving cycle for the target LG battery (18650HG2). The transfer learning SOC estimation results for the target LG battery (18650HG2) with the UDDS driving cycle in.

Fig. 8(b) and (g) are obtained using only the pre-training HWFET driving cycle data of the Samsung IN21700-30T battery. Table 4 summarizes the SOC estimation errors (MSE and MAE) for each method with the UDDS driving cycle. As listed in Table 4, the meta-learning SOC estimation shows the most accurate results (MSE of 0.0340% and MAE of 1.4499%) among the investigated estimation methods, although the driving cycles and specifications of pre-trained batteries used in the meta-learning are different from those of the target battery. Among investigated deep-learning methods, the DNN model shows the most inaccurate estimation results, with an MSE of 10.5744% and an MAE of 29.8901%, because it was not sufficiently trained (96 target battery data

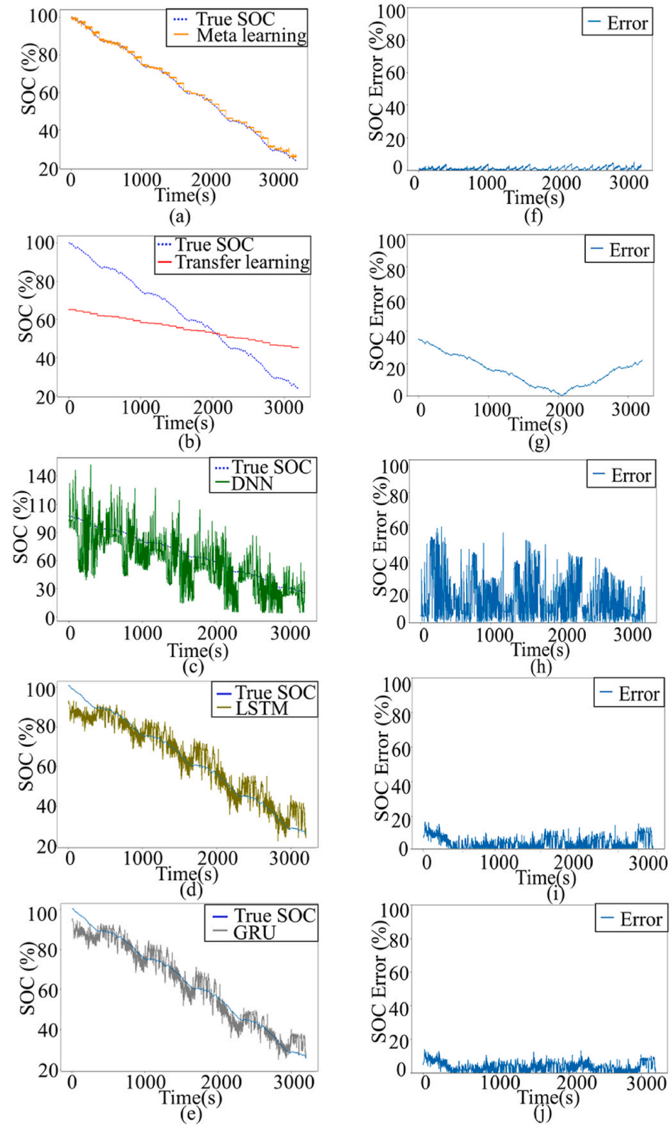

Fig. 7. SOC estimation performance evaluation at US06 Driving cycle (fine-tuned with 96 data points): (a) meta-learning result, (b) transfer learning result by pre-training Samsung IN21700-30T, (c) DNN result, (d) LSTM result, (e) GRU result, (f) meta-learning SOC errors, (g) transfer learning SOC errors by pre-training Samsung IN21700-30T, and (h) DNN SOC errors, (i) LSTM SOC errors, (j) GRU SOC errors.

points and nine gradient steps). As depicted in Fig. 8 (d), (e), (i) and (j), the SOC estimation results of LSTM and GRU models showed more accurate than those of transfer learning although their estimation results were less accurate than those of meta-leaning. Thus, LSTM and GRU models have effective performance for time-dependent SOC estimation tasks differently from a DNN model. However, LSTM and GRU models cannot estimate accurate SOC without a large amount of target battery training data. Table 5 lists the SOC estimation results for each method for the target LG battery (18650HG2) with an LA92 driving cycle. The same conditions, except for the driving cycle to be estimated, were applied in this experiment. As listed in Table 5, the most accurate SOC estimation method is again meta-learning, with an MSE of 0.04124% and an MAE of 1.5602%. Therefore, it can be concluded that meta-learning can accurately estimate the battery SOCs for various driving cycles.

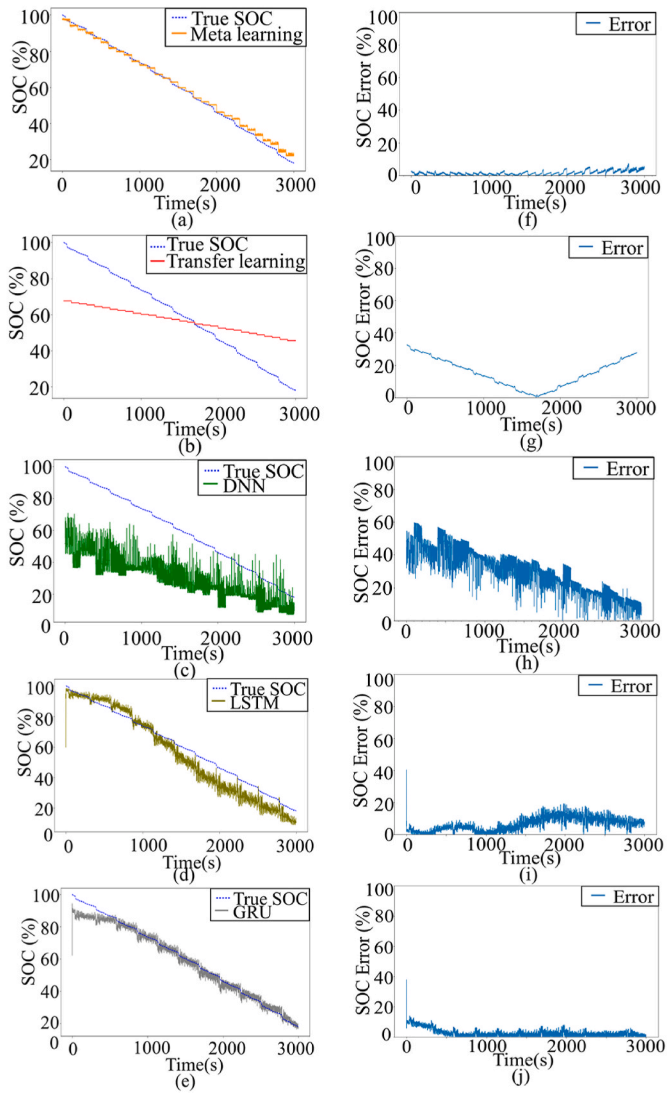

Fig. 8. SOC estimation performance evaluation at UDDS driving cycle (fine-tuned with 96 data points): (a) meta-learning result, (b) transfer learning result by pre-training Samsung (IN21700-30T, HWFET), (c) DNN result, (d) LSTM result, (e) GRU result, (f) Meta-learning SOC errors, (g) Transfer learning SOC errors by pre-training Samsung (IN21700-30T, HWFET), and (h) DNN SOC errors, (i) LSTM SOC errors, (j) GRU SOC errors.

Table 2
SOC estimation performance assessment in the US06 cycle fine-tuned with 8000 data points and nine gradient steps (Error rates in Fig. 6).

Meta learning	Samsung (IN21700-30T)	0.0127	0.9896
	Samsung (INR18650-20R)		
	Panasonic (NCR18650PF)		
Transfer learning	Samsung (IN21700-30T)	0.0426	1.4644
	Samsung (INR18650-20R)	0.0105	0.7864
	Panasonic (NCR18650PF)	0.0963	1.6754
DNN	N/A	0.0942	0.3451
LSTM	N/A	0.0050	0.0154
GRU	N/A	0.0086	0.0762

5. Conclusions

This paper presented a meta-learning Li-ion battery SOC estimation method that can significantly reduce the amount of required target battery data, by pre-training multiple battery data other than the target battery data. The proposed method is effective when the target battery training data are insufficient, specifically in the early stages of BMS development. Although a conventional battery-equivalent modeling-based SOC estimation method cannot use battery data different from that of the target battery, the proposed method has the advantage of being able to reuse other available battery data to pre-train a deep-learning model. Unlike other deep-learning SOC estimation methods with no pre-training in which only one type of battery is trained and the SOC of the same type of battery is estimated, the proposed meta-learning SOC estimation can predict target battery SOCs for pre-training different types and different driving cycles of battery data. In addition, the proposed method can estimate the battery SOC with a small amount of target battery data (96 data points) in only nine gradient steps of training. The proposed meta-learning SOC estimation, for which the best errors in the experiment were an MSE of 0.0176% and an MAE of 1.0075%, is superior to the transfer-learning SOC estimation, which also used pre-training under the same target battery training conditions (96 target battery data points and nine gradient steps), but resulted in an MSE of 3.1378% and an MAE of 15.1327%. Although this study mainly focused on applying meta-learning SOC estimation to Li-ion batteries with sloping OCV characteristics, such as Lithium Nickel–Manganese–Cobalt oxide (NMC) batteries, a future study may extend to the SOC estimation of Lithium iron phosphate (LFP) batteries with meta-learning. The accurate SOC evaluation of LFP batteries is challenging because of their flat OCV characteristics in the mid-range of SOC. Therefore, the meta-learning SOC estimation applied to LFP batteries may require modification to compensate for the inaccurate SOC estimation caused by these flat OCV features. However, evaluating the meta-learning for LFP battery SOC estimation would be meaningful because LFP batteries are rapidly rising in popularity in the EV market.

Table 3
SOC estimation performance assessment in the US06 cycle fine-tuned with 96 data points and nine gradient steps (Error rates in Fig. 7).

Method	Pre-training Data	MSE (%)	MAE (%)
Meta learning	Samsung (IN21700-30T)	0.0176	1.0075
	Samsung (INR18650-20R)		
	Panasonic (NCR18650PF)		
Transfer learning	Samsung (IN21700-30T)	3.1378	15.1327
	Samsung (INR18650-20R)	5.1763	18.7724
	Panasonic (NCR18650PF)	5.5178	19.4432
DNN	N/A	6.7153	20.0868
LSTM	N/A	0.8925	6.4132
GRU	N/A	0.3542	4.0124

Table 4
SOC estimation performance assessment in the UDDS cycle fine-tuned with 96 data points and nine gradient steps (Error rates in Fig. 8).

Method	MSE (%)	MAE (%)
Meta learning	0.0340	1.4499
Transfer learning	3.0109	15.0146
DNN	10.5744	29.8901
LSTM	0.8048	5.9112
GRU	0.3480	3.9642

Table 5
SOC estimation performance assessment in the LA92 cycle fine-tuned with 96 data points and nine gradient steps.

Method	MSE (%)	MAE (%)
Meta learning	0.04124	1.5602
Transfer learning	3.0518	15.1482
DNN	10.6561	29.8563
LSTM	0.5013	4.1821
GRU	0.4912	5.5131

CRediT authorship contribution statement

Daeung Jeong: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Sungwoo Bae:** Conceptualization, Formal analysis, Investigation, Validation, Resources, Supervision, Project administration, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Sungwoo Bae has patent BATTERY SOC ESTIMATION MATHOD AND DEVICE BASED ON META-LEARNING pending to Hanyang University.

Data availability

The authors do not have permission to share data.

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References

[1] F. Yang, W. Li, C. Li, Q. Miao, State-of-charge estimation of lithium-ion batteries based on gated recurrent neural network, Energy 175 (2019) 66–75, https://doi.org/10.1016/j.energy.2019.03.059.
[2] E. Chemali, P.J. Kollmeyer, M. Preindl, A. Emadi, State-of-charge estimation of Li-ion batteries using deep neural networks: a machine learning approach - ScienceDirect,(n.d.). https://www.sciencedirect.com/science/article/pii/S0378775318307080. (Accessed 10 May 2022).
[3] K.S. Ng, C.-S. Moo, Y.-P. Chen, Y.-C. Hsieh, Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries, Appl. Energy 86 (2009) 1506–1511, https://doi.org/10.1016/j.apenergy. 2008.11.021.
[4] N. Yang, X. Zhang, G. Li, State of charge estimation for pulse discharge of a LiFePO4 battery by a revised Ah counting, Electrochim. Acta 151 (2015) 63–71, https://doi.org/10.1016/j.electacta.2014.11.011.
[5] S. Lee, J. Kim, J. Lee, B.H. Cho, State-of-charge and capacity estimation of lithium-ion battery using a new open-circuit voltage versus state-of-charge, J. Power Sources 185 (2008) 1367–1373, https://doi.org/10.1016/j.jpowsour.2008.08.103.
[6] N.A. Windarko, J.-H. Choi, SOC estimation based on OCV for NiMH batteries using an improved takacs model, J. Power Electron. 10 (2010) 181–186, https://doi.org/10.6113/JPE.2010.10.2.181.
[7] S. Mian Qaisar, A proficient Li-ion battery state of charge estimation based on event-driven processing, J. Electr. Eng. Technol. 15 (2020) 1871–1877, https://doi.org/10.1007/s42835-020-00458-x.
[8] P. Spagnol, S. Rossi, S.M. Savaresi, Kalman filter SoC estimation for Li-ion batteries, in: 2011 IEEE International Conference on Control Applications, CCA), 2011, pp. 587–592, https://doi.org/10.1109/CCA.2011.6044480.
[9] Z. Liu, Y. Qiu, C. Yang, J. Feng, B. Jing, A parameter identification method for lithium-ion batteries using simplified impedance model and fractional order kalman filter, J. Electr. Eng. Technol. 17 (2022) 197–208, https://doi.org/10.1007/s42835-021-00887-2.
[10] G.L. Plett, Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification, J. Power Sources 134 (2004) 262–276, https://doi.org/10.1016/j.jpowsour.2004.02.032.
[11] G.L. Plett, Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation, J. Power Sources 134 (2004) 277–292, https://doi.org/10.1016/j.jpowsour.2004.02.033.
[12] Y. Xu, B. Hu, T. Wu, T. Xiao, Joint estimation of state of charge and state of health of lithium-ion battery based on fractional order model, J. Power Electron. 22 (2022) 318–330, https://doi.org/10.1007/s43236-021-00362-1.
[13] A. Manthopoulos, X. Wang, A review and comparison of lithium-ion battery SOC estimation methods for electric vehicles, in: IECON 2020 the 46th Annual Conference of the, IEEE Industrial Electronics Society, 2020, pp. 2385–2392, https://doi.org/10.1109/IECON43393.2020.9254918.
[14] W. Zhou, Y. Zheng, Z. Pan, Q. Lu, Review on the battery model and SOC estimation method, Processes 9 (2021) 1685, https://doi.org/10.3390/pr9091685.
[15] M.A. Hannan, M.S.H. Lipu, A. Hussain, A. Mohamed, A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: challenges and recommendations, Renew. Sustain. Energy Rev. 78 (2017) 834–854, https://doi.org/10.1016/j.rser.2017.05.001.
[16] N. Li, Y. Zhang, F. He, L. Zhu, X. Zhang, Y. Ma, S. Wang, Review of lithium-ion battery state of charge estimation, Global Energy Interconnect. 4 (2021) 619–630, https://doi.org/10.1016/j.gloei.2022.01.003.
[17] E. Chemali, P.J. Kollmeyer, M. Preindl, R. Ahmed, A. Emadi, Long short-term memory networks for accurate state-of-charge estimation of Li-ion batteries, IEEE Trans. Ind. Electron. 65 (2018) 6730–6739, https://doi.org/10.1109/TIE.2017.2787586.
[18] S. Shen, M. Sadoughi, M. Li, Z. Wang, C. Hu, Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries, Appl. Energy 260 (2020), 114296, https://doi.org/10.1016/j.apenergy.2019.114296.
[19] T. Tommasi, F. Orabona, B. Caputo, Learning categories from few examples with multi model knowledge transfer, IEEE Trans. Pattern Anal. Mach. Intell. 36 (2014) 928–941, https://doi.org/10.1109/TPAMI.2013.197.
[20] S.J. Pan, Q. Yang, A survey on transfer learning, IEEE Trans. Knowl. Data Eng. 22 (2010) 1345–1359, https://doi.org/10.1109/TKDE.2009.191.
[21] D.N.T. How, M.A. Hannan, M.S.H. Lipu, K.S.M. Sahari, P.J. Ker, K.M. Muttaqi, State-of-Charge estimation of Li-ion battery in electric vehicles: a deep neural network approach, in: 2019 IEEE Industry Applications Society Annual Meeting, 2019, pp. 1–8, https://doi.org/10.1109/IAS.2019.8912003.
[22] D. Darbar, I. Bhattacharya, Application of machine learning in battery: state of charge estimation using feed forward neural network for sodium-ion battery, Electrochem 3 (2022) 42–57, https://doi.org/10.3390/electrochem3010003.
[23] S. Bockrath, A. Rosskopf, S. Koffel, S. Waldhör, K. Srivastava, V.R.H. Lorentz, State of charge estimation using recurrent neural networks with long short-term memory for lithium-ion batteries, in: IECON 2019 - 45th Annual Conference of the, IEEE Industrial Electronics Society, 2019, pp. 2507–2511, https://doi.org/10.1109/IECON.2019.8926815.
[24] F. Yang, S. Zhang, W. Li, Q. Miao, State-of-charge estimation of lithium-ion batteries using LSTM and UKF, Energy 201 (2020), 117664, https://doi.org/10.1016/j.energy.2020.117664.
[25] X. Song, F. Yang, D. Wang, K.-L. Tsui, Combined CNN-LSTM network for state-of-charge estimation of lithium-ion batteries, IEEE Access 7 (2019) 88894–88902, https://doi.org/10.1109/ACCESS.2019.2926517.
[26] D.W. Chung, J.H. Ko, K.Y. Yoon, State-of-Charge estimation of lithium-ion batteries using LSTM deep learning method, J. Electr. Eng. Technol. 17 (2022) 1931–1945, https://doi.org/10.1007/s42835-021-00954-8.
[27] R. Zhao, P.J. Kollmeyer, R.D. Lorenz, T.M. Jahns, A compact unified methodology via a recurrent neural network for accurate modeling of lithium-ion battery voltage and state-of-charge, in: 2017 IEEE Energy Conversion Congress and Exposition (ECCE), 2017, pp. 5234–5241, https://doi.org/10.1109/ECCE.2017.8096879.
[28] A. Bhattacharjee, A. Verma, S. Mishra, T.K. Saha, Estimating state of charge for xEV batteries using 1D convolutional neural networks and transfer learning, IEEE Trans. Veh. Technol. 70 (2021) 3123–3135, https://doi.org/10.1109/TVT.2021.3064287.
[29] C. Vidal, P. Kollmeyer, E. Chemali, A. Emadi, Li-Ion battery state of charge estimation using long short-term memory recurrent neural network with transfer learning, in: 2019 IEEE Transportation Electrification Conference and Expo (ITEC), 2019, pp. 1–6, https://doi.org/10.1109/ITEC.2019.8790543.
[30] Y. Liu, J. Li, G. Zhang, B. Hua, N. Xiong, State of charge estimation of lithium-ion batteries based on temporal convolutional network and transfer learning, IEEE Access 9 (2021) 34177–34187, https://doi.org/10.1109/ACCESS.2021.3057371.
[31] J. Yosinski, J. Clune, Y. Bengio, H. Lipson, How transferable are features in deep neural networks?, ArXiv:1411.1792 [Cs], http://arxiv.org/abs/1411.1792, 2014.
[32] C. Finn, P. Abbeel, S. Levine, Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks, 2017. ArXiv:1703.03400 [Cs], http://arxiv.org/abs/1703.03400.
[33] F. Zheng, Y. Xing, J. Jiang, B. Sun, J. Kim, M. Pecht, Influence of different open circuit voltage tests on state of charge online estimation for lithium-ion batteries, Appl. Energy 183 (2016) 513–525, https://doi.org/10.1016/j.apenergy.2016.09.010.
[34] Y. Xing, W. He, M. Pecht, K.L. Tsui, State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures, Appl. Energy 113 (2014) 106–115, https://doi.org/10.1016/j.apenergy.2013.07.008.
[35] W. He, N. Williard, C. Chen, M. Pecht, State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation, Int. J. Electr. Power Energy Syst. 62 (2014) 783–791, https://doi.org/10.1016/j.ijepes.2014.04.059.
[36] P.J. Kollmeyer, A. Hackl, A. Emadi, Li-ion battery model performance for automotive drive cycles with current pulse and EIS parameterization, in: 2017 IEEE Transportation Electrification Conference and Expo (ITEC), 2017, pp. 486–492, https://doi.org/10.1109/ITEC.2017.7993319.
[37] P.J. Kollmeyer, Development and Implementation of a Battery-Electric Light-Duty Class 2a Truck Including Hybrid Energy Storage, Ph.D. disserta-tion, Univ. Wisconsin-Madison, Madison, WI, USA, 2015.
[38] P.J. Kollmeyer, M. Naguib, M. Skells, LG 18650HG2 Li-Ion Battery Data, Mendeley Data, Jan. 2020, 2020. https://data.mendeley.com/datasets/b5mj79w5w9/2.