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Transfer learning for battery smarter state estimation and ageing prognostics: Recent progress, challenges, and prospects

Kailong Liu [a], Qiao Peng [b], Yunhong Che [c,*], Yusheng Zheng [c,*], Kang Li [d], Remus Teodorescu [c], Dhammika Widanage [a], Anup Barai [a]

[a] WMG, The University of Warwick, Coventry CV4 7AL, United Kingdom
[b] Information Technology, Analytics & Operations Group, Queen's University Belfast, Belfast BT9 5EE, United Kingdom
[c] Department of Energy Technology, Aalborg University, Aalborg, Denmark
[d] School of Electronic and Electric Engineering, University of Leeds, LS2 9JT, United Kingdom

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ABSTRACT

With the advent of sustainable and clean energy transitions, lithium-ion batteries have become one of the most important energy storage sources for many applications. Battery management is of utmost importance for the safe, efficient, and long-lasting operation of lithium-ion batteries. However, the frequently changing load and operating conditions, the different cell chemistries and formats, and the complicated degradation patterns pose challenges for traditional battery management. The data-driven solutions that have emerged in recent years offer great opportunities to uncover the underlying data mapping within a battery system. In particular, transfer learning improves the performance of data-driven strategies by transferring existing knowledge from different but related domains, and if properly applied, would be a promising approach for smarter battery management. To this end, this paper presents a systematic review for the applications of transfer learning in the field of battery management for the first time, with particular focuses on battery state estimation and ageing prognostics. Specifically, the general issues faced by conventional battery management are identified and the applications of transfer learning to these issues are summarized. Then, the specific challenges of each topic are identified and the potential solutions based on transfer learning are explained, followed by a discussion of the state of the art in terms of principles, algorithm frameworks, advantages and disadvantages. Finally, future trends of data-driven battery management with transfer learning are discussed in terms of key challenges and promising opportunities.

1. Introduction

As a key technology to effectively bypass fossil fuels and promote carbon neutrality around the world by mid-century, batteries have been widely utilized in many renewable and sustainable energy applications [1,2]. Due to the superiority in terms of high energy density, low self-discharging rate, and virtually no memory effect, lithium-ion (Li-ion) battery is crucial not only for the energy transition but also for the decarbonisation of the transport sector [3–5]. For example, in the UK, battery plays a key role in achieving the mission to "put the UK at the forefront of the design and manufacturing of zero-emission vehicles" in the government's industrial strategy for the future of electric mobility [6].

However, battery is still considered as a "black box", where only a few external characteristic parameters are available via sensors, while the complex internal electrochemical reactions remain imperceptible [7–9]. Appropriate battery management solutions are necessary to estimate the internal states of battery such as state-of-charge (SoC), state-of-temperature (SoT), state-of-health (SoH), or predict the ageing dynamics of the battery (i.e., ageing trajectory, lifetime) and then effectively manage batteries to ensure that they can be operated reliably and safely. In this context, accurate battery state estimation and reliable battery ageing prognostics become the basis for the upper control strategy design [10,11], which are still long-term challenges for both academic researchers and industrial engineers and the bottleneck of the development of a smarter battery management system (BMS).

To date, numerous approaches have been designed to estimate battery states or predict battery ageing dynamics, which can be generally divided into model-based, data-driven, and hybrid methods [12,13]. Here the model-based methods attempt to simulate the internal electrochemical reactions of battery via physical or non-physical models [14], followed by the implementation of various system identification

* Corresponding authors.
E-mail addresses: kliu02@qub.ac.uk, Kailong.Liu@warwick.ac.uk (K. Liu), Qiao.Peng@qub.ac.uk (Q. Peng), ych@energy.aau.dk (Y. Che), yzhe@energy.aau.dk (Y. Zheng), k.li1@leeds.ac.uk (K. Li), ret@energy.aau.dk (R. Teodorescu), dhammika.widanalage@warwick.ac.uk (D. Widanage), a.barai@warwick.ac.uk (A. Barai).

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Nomenclature and abbreviations

AI	artificial intelligence
BMS	battery management system
BP	back propagation
CC-CV	constant current-constant voltage
CNN	convolution neural network
DoD	depth of discharge
EOL	end-of-Life
FOM	fractional-order model
GANN	generative adversarial neural network
GPR	Gaussian process regression
GRU	gated recurrent unit
HIs	health indicators
LSTM	long short-term memory
MMD	maximum mean discrepancy
MSDAN	multi-source domain adaptation network
NN	neural network
PDEs	partial differential equations
RMSE	root mean square error
RNN	recurrent neural network
SEI	solid electrolyte interface
SoC	State-of-Charge
SoH	State-of-Health
SoT	State-of-Temperature
TCA	transfer component analysis
TCN	temporal convolutional network
TL	transfer learning
ML	machine learning
LFP	lithium iron phosphate
NMC	lithium nickel manganese cobalt oxide
NCA	lithium nickel cobalt aluminium oxide
LCO	lithium cobalt oxide
BiGRU	bidirectional gated recurrent unit
EVs	electric vehicles
RBM	restricted boltzmann machine

algorithms to identify the correlated parameters for battery state estimation and ageing prognostics. An obvious limitation of the model-based methods is that the complicated partial differential equations (PDEs) or many model parameters involved need to be solved or identified, leading to huge computational cost [15]. In comparison with model-based ones, data-driven methods present the advantages that they are more flexible and can be easily implemented by technicians without much battery knowledge. This is mainly because this type of method is usually created by using a suitable dataset that covers the selected input features and outputs to train artificial intelligence (AI) or machine learning models. For the hybrid methods, the main logic is to improve the performance of battery state estimations or ageing prognostics by combining model-based and data-driven methods or different data-driven methods. In this context, data-driven methods also become the basis for the design of model fusion strategies in hybrid approaches to improve accuracy, robustness, and reliability. Therefore, data-driven methods have recently gained significant research focus to achieve effective battery management, especially from the perspective of battery state estimation and ageing prognostics.

The data-driven battery state estimation and ageing prognostics generally belong to supervised learning, which requires training the corresponding models with the selected input features and known outputs. For example, for battery SoC estimation, battery current, voltage, temperature, and charge quantity are generally utilized as the inputs while battery SoC is the output for model establishment. These parameters can also be selected for battery SoH estimation, in which case the battery SoH (or capacity) becomes the output. Another common solution for data-driven battery SoH estimation is to extract health indicators (HIs) from raw data as inputs to the model [16]. In addition, battery lifetime predictions also present two typical ways for data-driven modelling: one adopts the time-series forecasting method to capture battery capacity degradation trajectory, while the other adopts suitable features to fit the underlying mapping with battery End-of-Life (EoL). For linear cases, linear regression [17] and multiple linear regression [18,19] are widely used to capture the variation of the estimated battery parameters. But for nonlinear cases that are more general in real battery applications, more advanced machine learning algorithms are required to capture the strongly coupled nonlinear relationships. For example, support vector machine converts low-dimensional nonlinearity into a linear relationship in a high-dimensional space via a kernel function [20,21], and relevance vector machine utilizes a similar solution but can provide the probabilistic prediction results [22,23]. Gaussian process regression (GPR) is also one of the kernel-based machine learning methods, which is popular in battery SoC estimation [24,25] and ageing prognostics [26]. Here how to define a proper kernel to capture complicated nonlinear relationships in batteries becomes key for GPR-based battery applications. On the other hand, neural networks (NNs) are also good candidates as they are theoretically capable of capturing the complicated nonlinear relationships using various connected weights. Many types of NN are adopted for data-driven modelling in battery applications, such as feedforward NN, Elman NN, wavelet NN, long short-term memory (LSTM) NN, generative adversarial NN (GANN), and convolution NN (CNN) [27,28]. In summary, by deriving appropriate data-driven models based on these machine learning technologies, satisfactory battery state estimation and ageing prognostics can be achieved for specific battery cases. However, in real battery applications, the frequently changing load and operating conditions, different cell chemistries and formats, and complicated degradation patterns still pose a major challenge to expanding the applications of these methods in the battery management field [29]. Urgent efforts are needed to improve the evolving data-driven methods and make them more efficient and robust for different battery applications. To achieve this, by transferring the existing knowledge from different but related domains to the target of interest, transfer learning (TL) is becoming one of the most promising strategies for smarter and more efficient battery management. Taking NN as an example, TL can be conveniently implemented in NN to improve the accuracy and generalization of the trained NN model. Specifically, the main hindered relationships learned by the hidden layers can be retained by freezing these layers, while the new characteristics are quickly learned via retraining the last few fully connected layers, which benefits the accuracy and supports online training for battery states estimation and ageing prognostics [30]. In this context, the TL-based data-driven approach is becoming popular in the field of battery management recently to help implement the models trained in the laboratory to real battery applications.

To date, a few reviews have been published describing data-driven or AI-based applications for battery management (see Table 1). As SoH belongs to a key indicator of battery health, to better describe battery ageing dynamics, battery SoH is classified into the ageing prognostics part in this article unless otherwise stated. From these state-of-the-art reviews, on the one hand, it is clear that data-driven approaches are promising to handle lots of challenging issues such as state estimation and ageing prognostics in the field of battery management. On the other hand, although there are numerous research on data-driven or AI-based battery management, a systematic review focusing on TL-based battery applications and presenting an outlook on its recent progress, challenges, and prospects is still lacking. To date, TL has evolved into an efficient and powerful data-driven tool for smarter battery management. In this context, a timely review of TL-based battery management strategies is urgently needed to fill this survey gap.

Based upon the above discussion, a systematic review regarding different TL approaches and their applications in battery management, especially in two important but challenging areas, namely battery state

Table 1
Recent existing reviews related to data-driven and AI-based battery management.

Topic	Refs.	Content
State estimation	Manoharan et al. (2022) [31]	Review of several machine learning-based battery states estimation approaches
	Wang et al. (2020) [11]	General review of battery modelling techniques for battery state estimation
	Park et al. (2020) [32]	Overall review of different state estimation approaches in energy storage systems
	Hu et al. (2019) [33]	Review of battery key state estimation approaches
Ageing prognostics	Liu et al. (2022) [34]	General review of AI-based battery manufacturing and management including SoH estimation and trajectory predictions
	Li et al. (2022) [35]	General review of battery degradation and machine learning approaches
	Sui et al. (2021) [36]	General review of the non-probabilistic data-driven methods for battery SoH estimation
	Sulzer et al. (2021) [29]	General review of battery lifetime prediction regarding practical applications using field data
	Hu et al. (2020) [37]	Overall review of battery lifetime prediction approaches
	Li et al. (2019) [38]	SoH estimation and lifetime prediction of battery focusing on data-driven approaches
	Xiong et al. (2018) [39]	Overall review of battery SoH estimation approaches
	Lucu et al. (2018) [40]	General review of battery lifetime prediction approaches considering self-adaptive elements

estimation and ageing prognostics, are provided in this article. The review is intended to assist in both the selection of data-driven strategies and academic research plans, thus providing suggestions for future research and promoting progress in TL-based battery management at various readiness levels.

To be specific, the following topics will be covered in the review:

(1) A systematic framework for the use of TL in the field of battery management particular for battery state estimation and ageing prognostics is defined.
(2) For battery state estimation, after introducing the key challenges of each state estimation aspect, TL-based strategy and widely utilized tools for effectively estimating battery key states (SoC, SoT, and parameters) are presented and discussed.
(3) For battery ageing prognostics, after summarizing the key challenges of each battery ageing prediction-related application, classical TL-based strategies for battery SoH estimation, future ageing trajectory and lifetime prediction are presented, and their advantages and limitations are discussed.
(4) Current research gaps in the literature and remaining challenges for each aspect of data-driven battery management are summarized and discussed with several suggestions to accelerate future research of advanced TL-based battery management approaches.

The remainder of this article is organized as follows: Section 2 describes the basic concepts and fundamentals of TL, the general framework of using TL to benefit different directions (i.e., state estimation and ageing prognostics) of battery management. Section 3 focuses on the analysis and discussion of TL-based battery state estimation including SoC, SoT, and related parameters. In Section 4, TL-based battery ageing prognostics including battery SoH estimation, battery future ageing trajectory and lifetime prediction are presented. Section 5 summarizes the main challenges and suggests promising TL-based strategies for each aspect. Finally, Section 6 concludes this review.

2. Transfer learning-based battery management

This section first introduces the fundamentals of TL, followed by summarizing and defining a systematic framework for using TL in the field of battery management particular for battery state estimation and ageing prognostics.

2.1. Transfer learning fundamentals

TL is a popular research topic in the machine learning (ML) field, which focuses on taking advantage of knowledge from one condition and applying such knowledge to different but related conditions. From the application perspective, reusing or transferring information from previously learned tasks has the potential to significantly improve the training efficiency and model accuracy in new tasks [41]. In this section, the basic definitions of TL are given first for providing the preliminaries of TL to readers.

Definition 1. Domain and task. A domain $\boldsymbol{D}$ consists of two components, including a feature space χ and a marginal probability distribution $P(B)$ (where $X = \{x_1, x_2, \ldots, x_n\} \in \mathcal{X}$). A task can be represented by $T = \{y, f(x)\}$, which consists of the label space y and the target prediction function $f(x)$. The $f(x)$ is used to estimate the conditional probability $P(y|x)$ [42,43]. In battery state estimation and ageing prognostics, the domain mainly refers to the features and their distributions while the tasks are the estimated states or predicted lifetime. For example, in battery SoH estimation, the domain could be the HIs and the distribution of the HIs while the task is the estimation of battery SoH. The target prediction function refers to the machine learning model that maps the relationship between the health indicators and the SoH.

Definition 2. Learning transfer. Given a new learning task T_t based on the target domain D_t, it is possible to get some help from the source domain D_s and the previous learning task T_s. TL aims to improve the performance of predictive function $f_T(\cdot)$ for a new learning task T_t by discovering and transferring latent knowledge from D_s and T_s, where $D_s \neq D_t$ and/or $T_s \neq T_t$. Typically, the size of D_s is much larger than the size of D_t [44,45].

According to the transfer problems or solution ways, TL can be classified into different categories, as shown in Fig. 1. The specific differences among various categories are presented below. According to the definition of TL above, the main methods can be divided into three categories, which are inductive TL, transductive TL, and unsupervised TL depending on the availability of labelled data [45,41]. In inductive TL, although the target and source domains are similar, the target task is always different from the source task ($T_t \neq T_s$). Here the inductive TL is supposed to induce an objective prediction model $f_T(\cdot)$ by exploiting some labelled data in the target domain and taking advantage of the knowledge in D_s and T_s. For transductive TL, the tasks of both are the same ($T_t = T_s$), while the source domain and target domain present the difference ($D_t \neq D_s$). Here the transductive TL aims to improve the learning of the target prediction model $f_T(\cdot)$ using knowledge in D_s and T_s while no labelled data in the target domain are available. For the third unsupervised TL, the target task is different from but related to the source task ($T_t \neq T_s$). However, unsupervised TL focuses on solving unsupervised learning tasks in the target domain. In that case, no labelled data are available in both source and target domains during the training process.

Another classification method is to divide the TL into homogeneous one and heterogeneous one based on the similarity of both feature and label in source and target space. Under this concept, when $X_t = X_s$ and $\mathcal{Y}_t = \mathcal{Y}_s$ while only marginal probability has differences, the scenario is called homogeneous TL. Otherwise, when $X_t \neq \mathcal{X}_s$ and/or $\mathcal{Y}_t \neq \mathcal{Y}_s$, it belongs to heterogeneous TL.

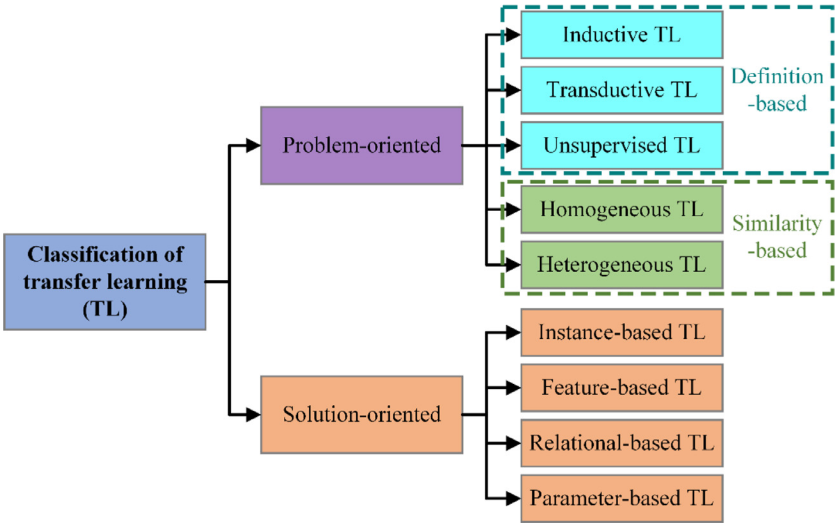

Fig. 1. Categories for different TL approaches.

The above two categorization methods could be seen as problem-oriented classification method, which mainly considers the differences between target and source space. To consider the solutions, the TL methods can be divided into the following four groups: instance-based, feature-based, relation-based, and parameter-based approaches [46,47]. Instance-based TL transfers the knowledge based on the instance reweighting strategy, which assumes that the data in the source space can be reweighted to facilitate the task in the target space. Feature-based TL transfers the original features to generate a new feature representation, which can be further divided into two categories. The first calls the asymmetric feature transformation to transfer the source features to match the target features via reweighting. The second attempts to find common latent feature mapping for both source space and target space, which can be called the symmetric feature transformation. Relation-based TL transfers the learned logical relationship or rules in source space to target space. Problems of relational domains are the focus of this kind of TL. The last category, parameter-based TL, assumes that the tasks of source space and target space share some parameters or prior distributions of the hyper-parameters of the model, where the pre-trained parameters in the source domain help to accelerate the convergency in the target domain.

2.2. Battery management applications with transfer learning

In battery management applications for battery state estimations and ageing prognostics mainly include feature-based TL and parameter-based TL, based on the solution-oriented classification of TL. If the problem-oriented classification is applied, TL strategies in battery management generally include inductive TL and transductive TL. Despite different classifications, feature-based TL presents some similarities with inductive TL and parameter-based TL is analogous to transductive TL. Therefore, in this review, feature-based TL and inductive TL can be considered as the same type of TL that applies a domain adaptation strategy to achieve TL. Parameter-based or transductive TL refers to a different type of TL that realises TL through a fine-tuning strategy. The role of domain adaptation and fine-tuning strategies in battery state estimations and ageing prognostics can be illustrated in Fig. 2.

The goal of domain adaptation is to minimize the discrepancy in feature distribution between the source domain and the target domain so that the generalization and accuracy of data-driven models can be improved [47]. In general, there are two important ways to implement domain adaptation in battery state estimation and health prognostic, as shown in Fig. 2. The first way is to use the symmetric feature transformation to transform the features in the source and target domains into a common latent feature space, where the discrepancy of features from both domains can be minimized. The other opinion is to integrate the loss for domain discrepancy into the overall loss of machine learning algorithms to improve model adaptation in the target domain.

For fine-tuning strategies, the main idea is to retrain an already trained data-driven model by adding new information from different scenarios to the model. Specifically, only a small amount of data from the target battery or target operating conditions will be used for model re-training to further improve the accuracy of a data-driven model. The fine-tuning strategy is based on the assumption that the general correlations between the input parameters and output state are similar in both the source and target domains. From the perspective of the internal electrochemistry of the battery, similar electrochemical reactions occur inside the cell during normal battery operation, and the battery states under some specific conditions could be estimated by fine-tuning the existing data-driven model using only a small amount of data in the target domain. In this way, the data-driven model can be adapted to new scenarios that differ from those in the source domain. In Fig. 2, a NN is used as an example to illustrate the principle of fine-tuning strategy, where the parameters in either top layers or shallow layers can be adjusted during the retraining process.

The general framework for transfer learning-based battery state estimation and ageing prognostics is shown in Fig. 3. To be specific, the data from both the source and the target batteries will be first cleaned with several pre-processing steps, including abnormal values deletion, miss values filling, data alignment and smoothing, etc. Then, the feature extraction process is conducted, where the original features or the domain-adapted features using the symmetric feature transformation methods mentioned above are extracted. Thirdly, the base model is trained using the data from the source batteries. After that, two general methods can be chosen for transfer learning strategy implementations. The first is model-based transfer learning, which retrains some of the parameters of the base model using available labelled data from the target battery to fit the new application scenario. The other is the feature domain adaptation to improve the model generalization, which reduces domain discrepancy between the outputs of the hidden states of the neural network by reducing the loss that describes the difference between the source battery and the target battery. Finally, the transferred model is used for state estimations or ageing prognostics by inputting the features extracted from the target batteries.

3. Transfer learning-based battery state estimation

For safe, efficient, and reliable battery system control, battery parameters and states should be monitored in a timely manner in online battery management. In general, the development of a data-driven method

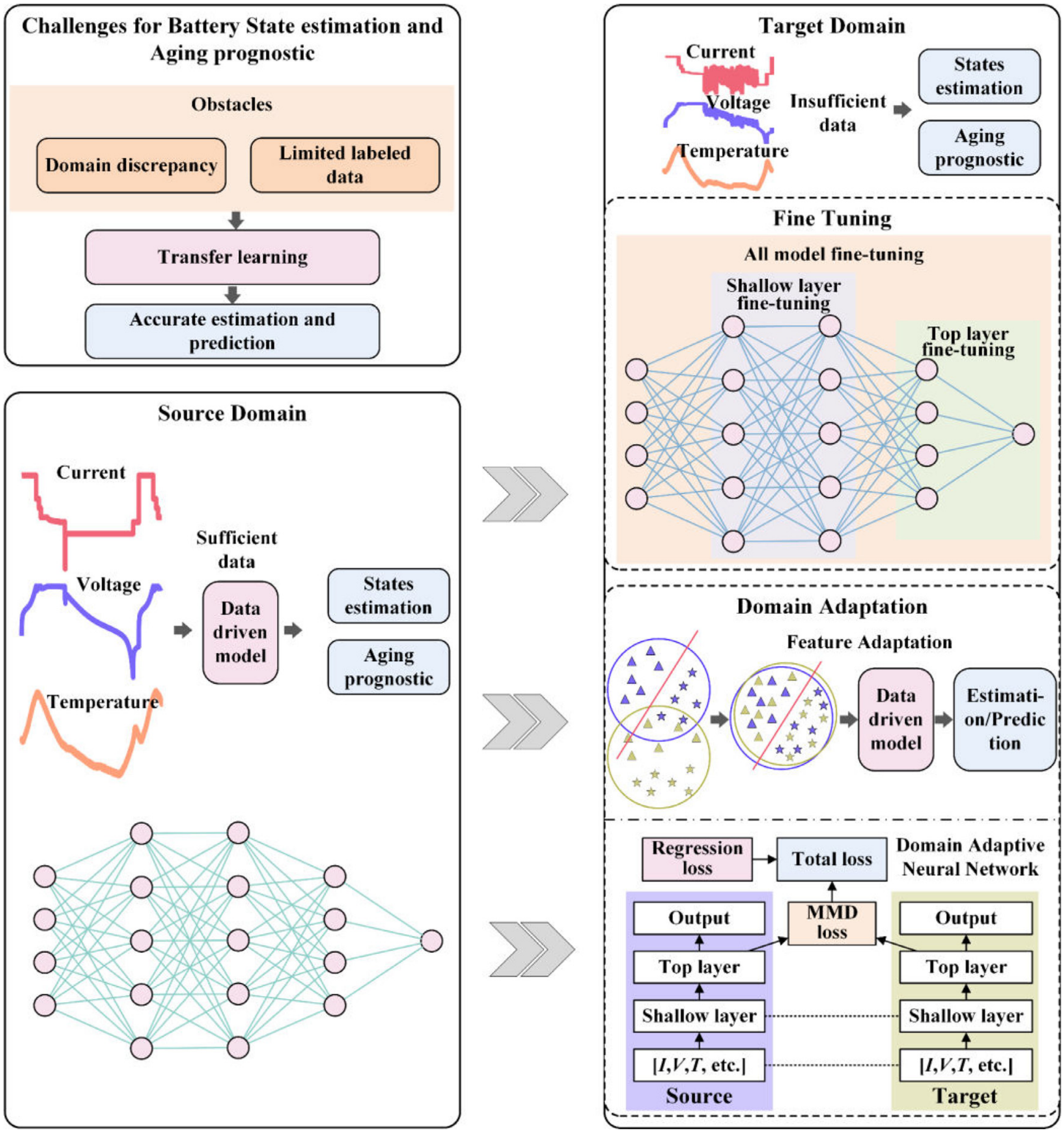

Fig. 2. TL in battery state estimation and ageing prognostic.

for estimating battery parameters and states involves the training process based on the training dataset (i.e., the source domain) and the testing evaluation based on the validation dataset (i.e., the target domain). However, discrepancies between the source and target domains and the lack of labelled data in the target domain make accurate and reliable battery state estimation difficult. The general challenges in traditional data-driven battery state estimation methods and the role of TL are illustrated in Fig. 4.

Specifically, the discrepancies between the source domain and the target domain exist in the following three aspects. Firstly, the properties of batteries vary with cell chemistry, format, and manufactural inconsistency, resulting in different voltage and temperature responses. Therefore, variations in the internal states of different cells will be different even under the same operating conditions. Secondly, external environmental conditions, such as ambient temperature and humidity, affect the internal electrochemistry of batteries. Different internal electrochemical reactions lead to different battery dynamics when the load is changed. In this way, the correlation between the measurable signals (i.e., current, voltage, ambient temperature) and the battery states will also vary. Thirdly, in real applications, batteries are subjected to different loading profiles, so the battery voltage and temperature respond differently to the different loading profiles. The differences in voltage and temperature response also lead to different mapping relationships between the measurable parameters and the internal states. The above three factors contribute to different data distributions in the source and target domains, which reduces the estimation accuracy of the pre-trained data-driven model in the target domain. Moreover, there is also a lack of labelled data in the target domain in real applications. The limited labelled data makes it difficult to effectively train a new data-driven model, so the model accuracy in state estimation cannot be guaranteed.

TL is an effective way to overcome the challenges summarized above. In terms of domain discrepancy, TL is a powerful strategy to reduce the difference between the source domain and target domain so that the performance of the model in the target domain can be greatly improved. The information from the source domain can be applied to accelerate the convergence of the retraining process and ensure the accuracy of the estimation in the target domain. In the following sections, the specific challenges and TL-based solutions for estimating different battery states are summarised and evaluated in detail.

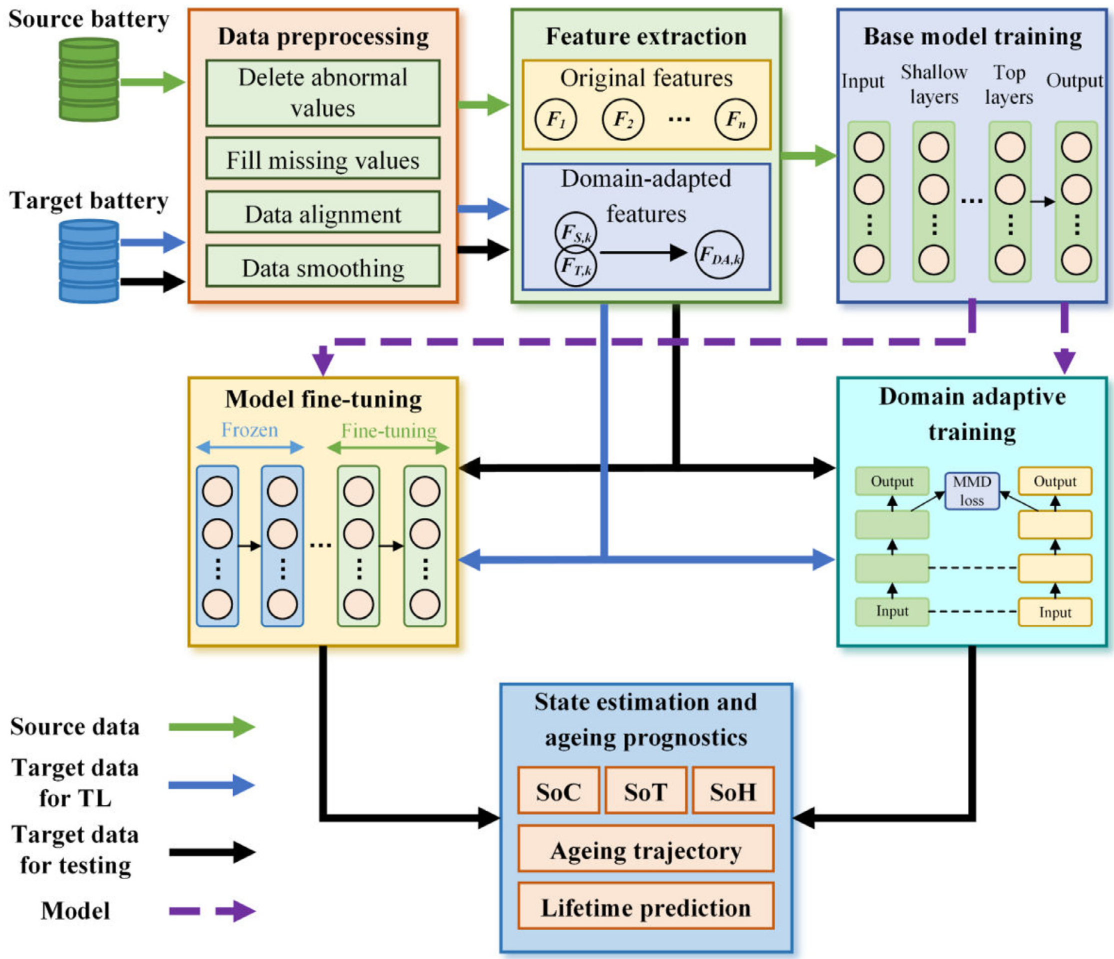

Fig. 3. General framework for data-driven battery states estimation and ageing prognostics with transfer learning.

3.1. SoC estimation with transfer learning

3.1.1. SoC estimation role and challenges

General data-driven estimation process: Battery SoC, defined as the current available capacity expressed as the percentage of the total battery capacity, is one of the key states to evaluate battery remaining capacity during operations [48]. SoC is capable of providing prior knowledge for the management of charging/discharging, balancing, and other operations to guarantee the safe and reliable operations of batteries. However, battery SoC is rapidly varied but difficult to be measured while other parameters such as current and voltage can be measured by BMS. Data-driven methods for estimating battery SoC aim to map the hidden relationships between these measured parameters and battery SoC. Generally, current, voltage, and temperature are set as inputs, while SoC is the output to train a data-driven model. Then the well-trained model can be used to estimate SoC when new measured data is available.

Key challenges regarding SoC estimation: Data-driven battery SoC estimation has developed rapidly in recent years due to its flexibility and strong non-linear mapping capability. Another benefit is that data-driven methods can avoid the complex parameter calibration required by model-based methods, making data-driven solutions more suitable for online applications. However, there are still some obstacles that limit the wider application of data-driven methods for battery SoC estimation, and the key issues are summarized as follows:

(1) **Data acquisition**. It is difficult to measure the SoC of batteries directly and to establish a relationship between the measured parameters and battery SoC. Furthermore, most measured data cannot be used for data-driven model training due to the low sampling frequency and high noise in real applications, which is a general problem that hinders the progress of research.
(2) **Battery degradation**. Batteries undergo degradation over the course of use, leading to a decrease in nominal capacity and different internal electrochemical reactions in various ageing states. According to the definition of SoC, the real battery capacity significantly affects the SoC value. Therefore, the data-driven models trained using training data for specific ageing states usually cannot estimate the SoC of the battery throughout its life cycle.
(3) **Variable loading profiles and ambient**. Batteries in real applications are subject to complex dynamic current profiles and varying ambient temperatures. The voltage response and SoC change patterns are different under different conditions. For example, decreasing battery capacity at low temperatures causes the SoC variation pattern to be different from that at room temperature. In this context, it becomes difficult for the data-driven models developed for specific operating scenarios to accurately estimate the SoC of batteries under different working conditions.
(4) **Various battery types**. Models trained with data from one type of battery would not work well with other types of batteries with different chemical properties and capacities because of the different electrochemical properties. Here, the voltage and temperature responses change for the same charging current and degrade the performance of the SoC estimation.

It should be known that these four challenges in data-driven SoC estimation also exist in model-based estimation and are difficult to

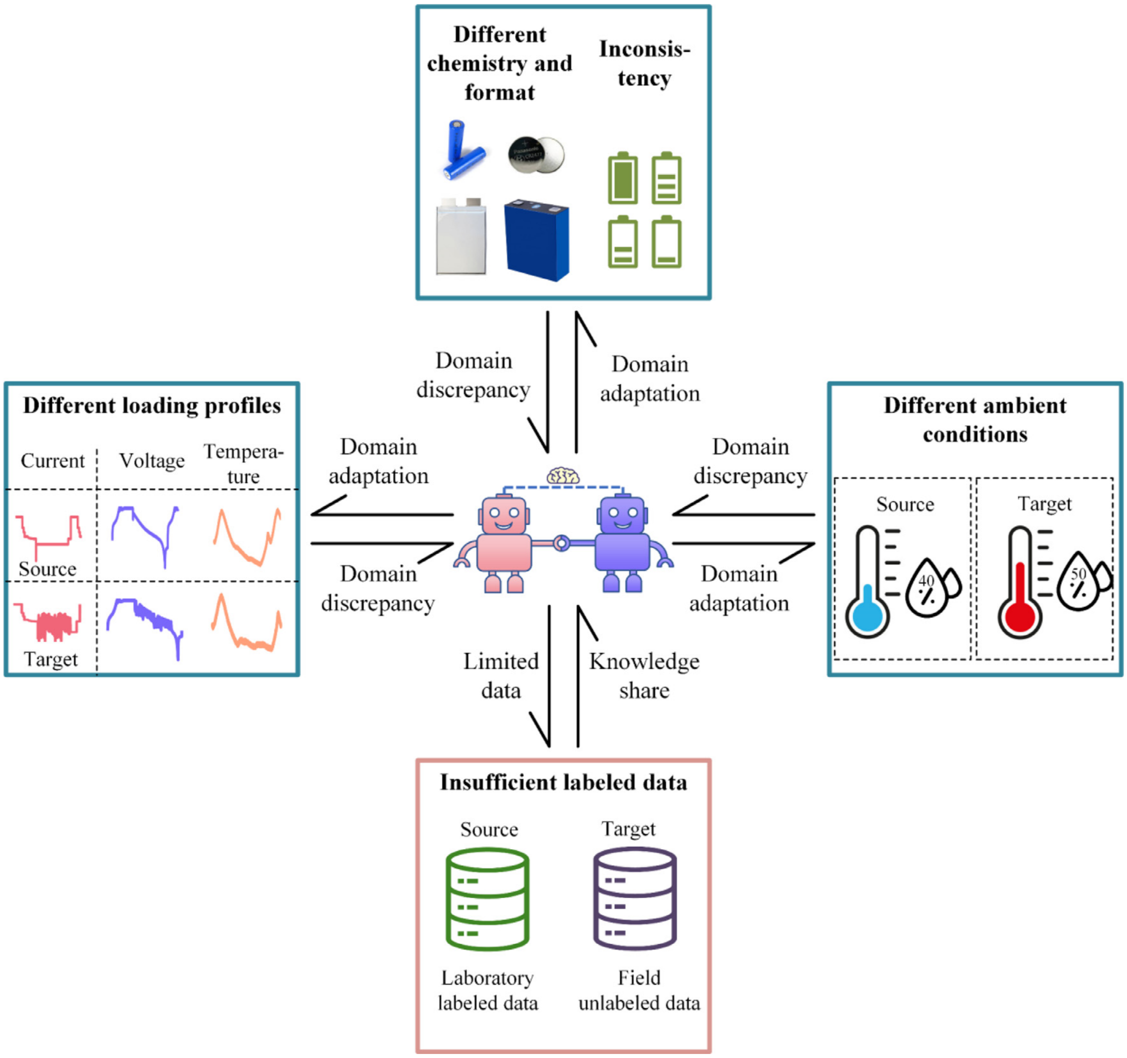

Fig. 4. General challenges for battery state estimation and the role of TL.

overcome without increasing model complexity. However, after integrating the TL strategy into the data-driven methods, the pre-trained data-driven SoC estimation model and the newly acquired data from test batteries could be well used to improve the adaptability of the model to a new battery cell without making the original model significantly more complex.

3.1.2. Transfer learning-based SoC estimation

In the existing literature, there are various TL-based battery SoC estimation methods, which can be mainly divided into the model parameter fine-tuning strategy and the domain adaptation strategy, depending on how they realise the TL.

Fine-tuning strategy: Fig. 5 illustrates a typical process of fine-tuning strategy-based battery SoC estimation. The non-linear mapping between input data such as current, voltage, temperature, and output SoC is learned by training a machine learning model. There are two ways to fine-tune the parameters of a data-driven model for battery SoC estimation. The first is to treat the parameters of a pre-trained model as initial values for the target battery, as shown in Fig. 5 (a) [49]. All the parameters from a pre-trained data-driven model can serve as prior knowledge when new data from the target domain are used to re-train this model. With this prior knowledge, the retraining process can be accelerated as this knowledge makes it easier to find the new local optimum when the data-driven model is re-trained for the target task. This idea has been studied and implemented for battery SoC estimation at different temperatures and dynamic discharging profiles, based on a temporal convolutional network (TCN) model [50]. All parameters fine-tuning strategy is also applied for the SoC estimation for different battery types based on other types of NNs such as the LSTM [51] and gated recurrent unit (GRU) NN [49], with satisfactory accuracy improvement. Besides, the strategy of fine-tuning all the model parameters can also be adopted in a self-supervised learning framework for battery SoC estimation, where the unlabelled data is used to help accelerate the convergence when retraining the model with the labelled data [52].

Another way to realize fine-tuning strategy-based TL for battery SoC estimation is to fix some parameters of the pre-trained model and fine-tune other parameters for new applications. For NN cases, either shallow layers or top layers of the NN could be frozen and the other in the network can be set as adjustable. In some references such as Ref. [53], the shallow LSTM layer is frozen after pre-training and only the fully connected layer is retrained to improve the accuracy of SoC estimation, as shown in Fig. 5(b). In other cases, the top fully connected layers are frozen while the other layers can be retrained. This fine-tuning method has been implemented in Ref. [54] to estimate SoC during the charging process considering different battery types and ageing status by adjusting the parameters in shallow 1D CNN layers. Such a fine-tuning method has been also applied in Ref. [55] for SoC estimation with different battery types and temperatures under dynamic working conditions.

Domain adaptation: There are two ways to implement domain adaptation in battery SoC estimation. One aims to reduce the feature

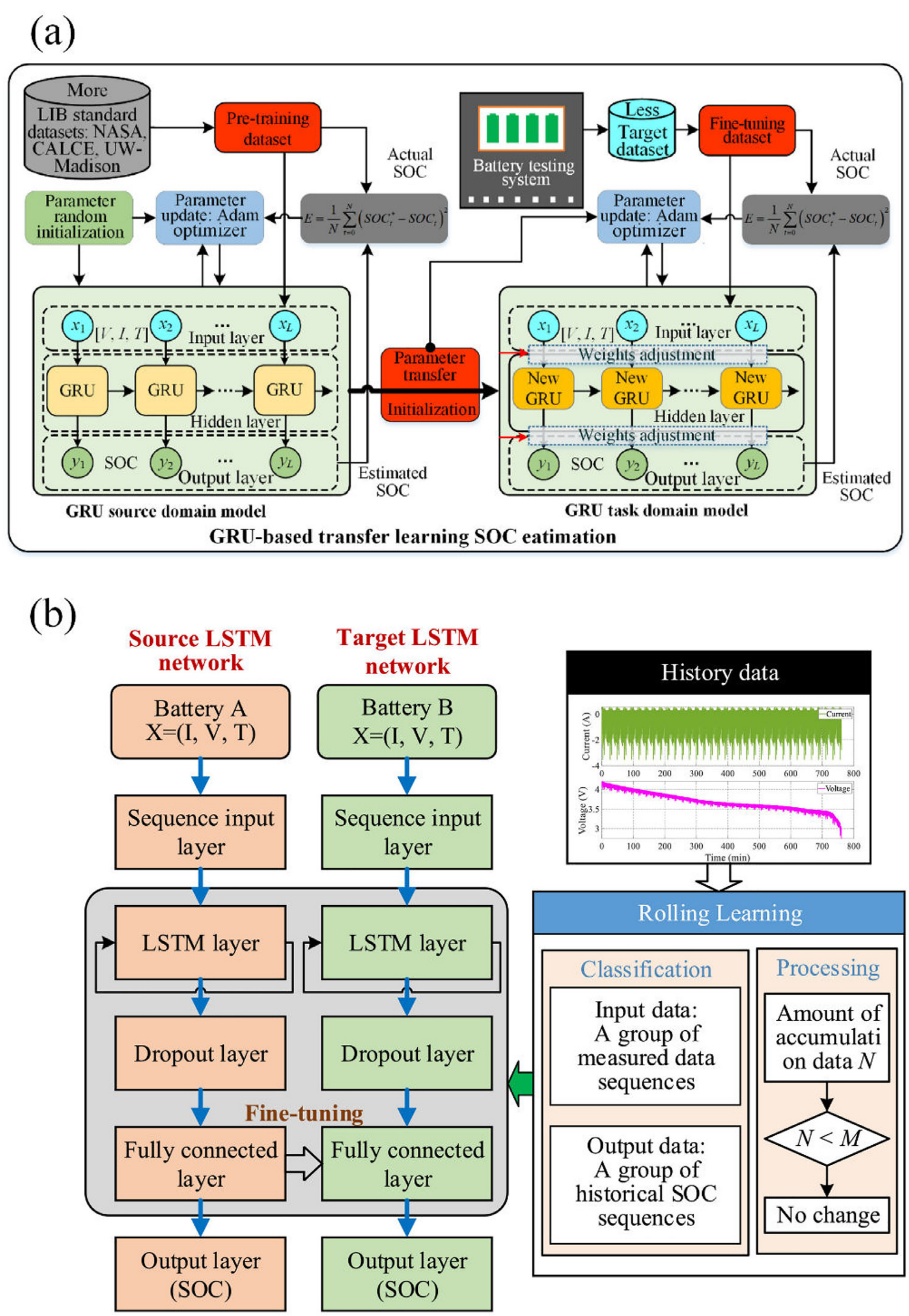

Fig. 5. Typical process of fine-tuning-based TL for battery SoC estimation: (a) All parameters fine-tuning strategy [49], (b) Partial layer fine-tuning [53].

discrepancy in the feature extraction and selection process. For instance, similar features of the source battery and the target battery are selected. The selected features are then used as input into the data-driven model to ensure the accuracy of the battery SoC estimation at different temperatures [56]. Another way to implement domain adaptation is to incorporate the maximum mean discrepancy (MMD) as an additional loss in the NN to reduce the discrepancies in the domain-shared features, as illustrated in Fig. 6 [57]. The MMD is a non-parametric distance metric that has been used in TL to measure the discrepancy between the data distributions in the source and target domains [58,59]. For example, the MMD is used on the top of CNN layers, bidirectional LSTM layers, and fully connected layers to add additional losses when training for the multiscale domain adaptation [59], which helps to improve the SoC estimation accuracy of different battery types. The results also indicate the superiority of the multiscale domain adaptation in comparison with the fine-tuning strategy. Another related work considers both MMD loss for domain adaptation and fine-tuning strategy to improve the SoC estimation accuracy of different battery types under constant current working conditions [57].

Table 2 summarises some typical studies on TL-based battery SoC estimation, which include the corresponding data characteristics in both source and target domains, the data-driven model, and the TL strategy. It can be seen that different types of NNs have been used as the data-driven model to implement TL for battery SoC estimation. Among all TL strategies, the fine-tuning strategy is more popular than domain adaptation because it is easy to implement and provides satisfactory performance in the target domain. The analysis of the data characteristics of the source and target domains also suggests that existing works mainly focus on the

Table 2
Summary of TL-based battery SoC estimation.

Refs.	Source Domain	Target Domain	Model	Strategy
Ref. [49]	* NMC (2 Ah) battery with DST, FUDS, US06, and BJDST at 0°C, 25°C and 45°C * NCA (2.9 Ah) battery with UDDS, LA92, US06, and HWFET at -20°C, -10°C,0°C,10°C, and 25°C * LCO (2 Ah) battery with CC at 4°C, 24°C and 44°C	NMC (3 Ah) battery with CC, FUDS, US06, and UDDS at 25°C, 32°C, 36°C, 42°C, and 52°C	GRU	Fine-tune all layers of the pre-trained model
Ref. [50]	NCA battery with FTP, UDDS, LA92, US06, and HWFET.	NCA battery with Hybrid drive cycles	TCN	Fine-tune all layers of the pre-trained model
Ref. [51]	Partial data	Full data	LSTM	Fine-tune all layers of the pre-trained model
Ref. [52]	NMC battery with unlabelled data	NCA battery with labelled data	DNN	Fine-tune all layers of the self-trained model
Ref. [53]	NMC battery with UDDS at 30°C	* NMC battery with FUDS at variant temperatures * LCO battery with US06 at 25°C * NMC battery with FUDS and UDDS at 25°C when SOH reaches 96.3%, 89.5%, and 87.3%	LSTM	Fine-tune the last fully connected layer of the pre-trained model
Ref. [54]	LFP (20 Ah) battery with 0.3C based CC-CV charge at fresh stage	* LFP (20 Ah) battery with 0.3C based CC-CV charge at the aged status * LFP (27 Ah) battery with 1C-based CC-CV charge at fresh stage	CNN	Fine-tune the CNN layer of the pre-trained model
Ref. [55]	NCA (2.9 Ah) battery with UDDS, LA92, US06, HWFET, and mixed profiles from -25°C - 25°C	NMC (3 Ah) battery with UDDS, LA92, US06, HWFET, and mixed profiles from -20°C - 40°C	CNN	Fine-tune the CNN layer of the pre-trained model
Ref. [56]	NCA (2.9 Ah) battery with dynamic profiles at 10°C	NCA (2.9 Ah) battery with dynamic profiles at 25°C, 0°C, -10°C, and -20°C	LSTM	Adapt input features
Ref. [59]	NCA (2.9 Ah) with UDDS, LA92, US06, HWFET, and mixed profiles from -25°C - 20°C	* NMC (2Ah) with DST, US06, and FUDS from 0 °C to 50 °C. * NMC (2Ah) with BJDST, US06, and FUDS at 0°C, 25°C, and 45°C.	CNN, BiLSTM	Add MMD loss on the top of CNN, LSTM, and fully connected layer
Ref. [57]	LFP (1.1 Ah) with constant current profiles at the fresh stage	LFP (1.1 Ah) with constant current profiles at the aged stage	LSTM	Fine-tune the LSTM layer of the pre-trained model and add MMD loss on a fully connected layer

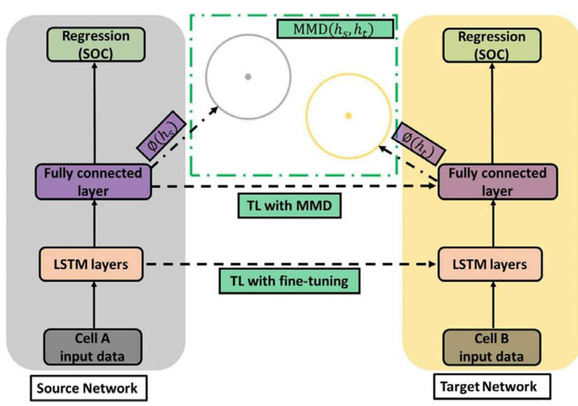

Fig. 6. Typical framework of domain adaptative NN for battery SoC estimation [57].

transfer of the pre-trained model when the battery chemistry is similar. The transfer of the model at different battery chemistries and formats and under different working conditions needs to be further investigated.

3.2. SoT estimation with transfer learning

3.2.1. SoT estimation role and challenges

Definition: To date, there is no strict definition in the literature for battery SoT. The SoT can be characterised either by the volume-averaged temperature (i.e. the volume temperature), the internal temperature, or the temperature distribution. Monitoring the battery SoT during operation is of utmost importance for the safe, efficient, and durable operation of the battery system. For example, if the battery temperature exceeds the safety threshold at high operating rates, thermal hazards such as thermal runaway can be triggered, with catastrophic consequences. In cold climates, the performance of LIBs is undermined due to slow electrochemical reactions inside the cell [60,61], leading to a dramatic decline in the available energy and power [60,62]. Furthermore, charging batteries at low temperatures can trigger lithium plating, which renders accelerated battery degradation and can lead to inter short-circuit [9,63]. At elevated temperatures, side actions such as the growth of solid electrolyte interface (SEI) become significant, giving rise to the consumption of cyclable lithium and accelerated battery capacity fade [9,64]. For this reason, it is important to keep the battery temperature within an optimal operating range through thermal control, and monitoring the SoT is a fundamental task in the battery management system. However, battery SoT cannot be measured directly by the surface-mounted temperature sensors, as they cannot keep track of the rapid fluctuations in internal temperatures due to the delay in heat transfer from the battery core to the surface. In large format LIBs, the temperature gradient inside the cell becomes apparent due to the considerable heat generation rates and the long heat transfer path, especially at high operating rates. The difference between the internal temperature and the surface temperature can be 10 °C or even more. Nevertheless, due to the high cost and technical challenges, it is not possible to install more that a few temperature sensors in the battery cell to obtain the SoT information directly. Therefore, credible estimation of battery SoT is an important and challenging issue in battery management.

Key challenges regarding SoT estimation: Data-driven SoT estimation has evolved in recent years due to its flexibility and ease of implementation. Compared to model-based methods, data-driven SoT estimations bypass the need to know the complicated thermal dynamics within the battery cell and pack. With model-based estimation, it is quite difficult to accurately model the thermal dynamics of the battery, including heat generation, heat accumulation, and heat dissipation, as these thermal processes vary depending on battery chemistry, geometry and cell arrangement in a battery pack. Data-driven estimation, on the other hand, can achieve accurate estimation by exploring the underlying patterns in the training dataset and mimicking the non-linear mapping relationship between the input data and the target data (i.e. the battery SoT in this scenario). Moreover, data-driven SoT estimation avoids the complicated process of model parameterisation, which is one of the most important procedures in model-based estimation and may be different for various thermal models. In the context of data-driven estimation, the training process is the same for different applications, which allows learning the highly non-linear relationships between the inputs and outputs in the dataset. Nevertheless, there are still some key challenges in traditional data-driven SoT estimation, which can be summarised as follows:

(1) **Data acquisition**. It is difficult to obtain sufficient data for data-driven SoT estimation model training in some estimation scenarios. In particular, during core temperature estimations, the data of the battery's internal temperatures are needed and used as labelled data for model training. However, obtaining such data on the internal temperature of the battery is a technical challenge, as suitable temperature sensors have to be inserted into the interior of the cell without damaging the battery cell.
(2) **Battery degradation**. Battery degradation will bring challenges to the data-driven model trained based on the data from fresh batteries. Batteries inevitably degrade during usage, and there will be an increase in internal resistance and then heat generation. In this context, the SoT of an aged battery will differ from that of a fresh cell. As a result, it becomes difficult for the data-driven model, which is trained using data in the early stages of battery life, to accurately estimate the SoT of the battery throughout its life cycle.
(3) **Complex loading profile and ambient conditions**. in real applications, batteries are operated under variable and complicated current profiles, different ambient temperatures, and different cooling cases, so the SoT of batteries is different under various conditions. For example, under different current profiles, the heat generation rates inside the cell are different, so the temperature response of a battery will also become different. At low temperatures, the battery temperature increases more than that in higher temperature environments for the same current profile due to the much higher internal resistance. In addition, the increase in battery temperature is lower with forced convective cooling than that in natural convective cooling due to the increased heat dissipation. However, the training dataset cannot cover all possible operating scenarios with different current profiles, ambient temperatures, and cooling conditions, so data-driven models trained under the limited operating conditions will fail when estimating battery SoT under other new situations.
(4) **Various battery types**. data-driven models trained on experimental data from one battery type cannot provide accurate SoT estimation for other battery types due to differences in cell chemistry, format, and capacities. From the perspective of the thermal dynamics within the cell, the heat generation rate of the different battery cells will be distinct due to the different internal resistance, while the heat accumulation also varies due to various thermal mass of the different cells. In addition, different cell geometries lead to various temperature distributions within the cell. These factors contribute to the SoT of the battery being different even under the same operating conditions. In terms of data characteristics, experimental data from different battery cells will also be completely different. For example, at the same operating rate, the current value of a larger-capacity cell will be much higher than that of a smaller-capacity cell. Moreover, the operating voltage range is different for batteries with different chemical compositions (e.g. 2.0-3.6 V for LFP cells, 2.5-4.2 V for NMC cells). Therefore, it is difficult for a data-driven model trained on the experimental data of one type of battery to estimate the SoT of other types of battery cells.

The aforementioned challenges limit the accuracy and generalisability of data-driven models in SoT estimation. It is imperative to develop new methods that are capable of making use of the limited training data to accurately estimate the SoT of batteries under different ageing states, operating conditions and battery types. TL offers a great opportunity to overcome these obstacles by transferring the pre-trained data-driven SoT estimation model to other scenarios without the need for a large amount of data from the target domain. The estimation of battery SoT in different scenarios can also be improved by adapting the pre-trained model to the target case.

3.1.2. Transfer learning-based SoT estimation

The application of TL on battery SoT estimation has seldom been investigated so far despite its promising prospect. Fine-tuning strategy and domain adaptation will still be two main approaches for achieving model transferring in SoT estimation. A representative study on TL-based SoT estimation was explored by Wang et al. [65]. In Ref. [65], an LSTM NN in combination with fine-tuning strategy was implemented to estimate the core temperature of batteries under different current profiles. The estimation framework was illustrated in Fig. 7. Specifically, the data from the constant current-constant voltage (CC-CV) charging and constant current discharging tests of a cylindrical battery between −10-55 °C was collected and used as training data to train the base model. A temperature sensor was intruded into the battery core by drilling a hole to measure the core temperature variation during battery operations. The current, voltage, surface, and ambient temperatures were treated as input, and the core temperature was the output of the LSTM NN. The pre-trained model was then transferred to estimate the core temperature of the battery of the same type but with a different batch number under other current and temperature conditions. The data-driven model was transferred to the target domain by fine-tuning the parameters of fully connected layers using a small amount of data from the target domain.

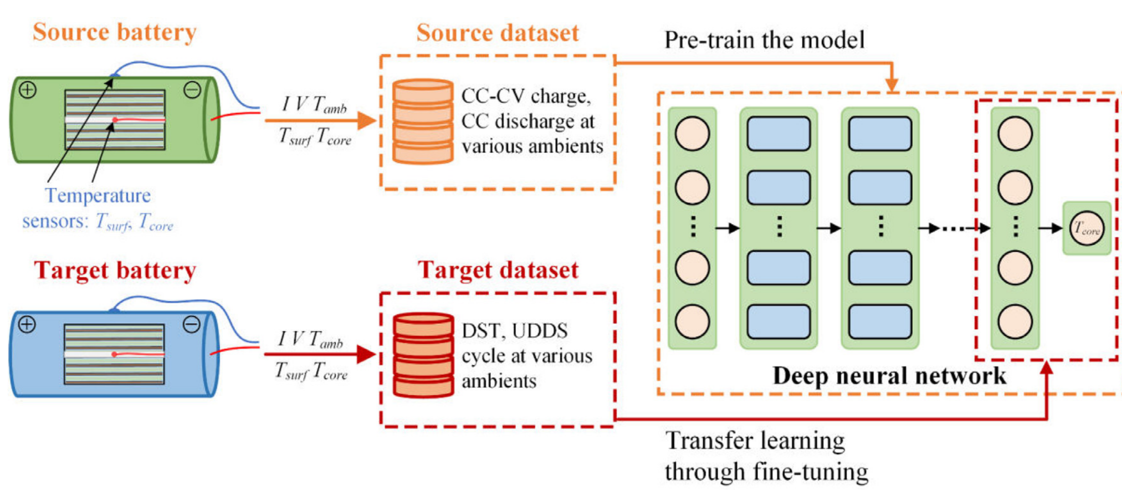

Fig. 7. Core temperature estimation of batteries based on LSTM with TL strategy [65].

Their results suggested that higher accuracy can be achieved with TL and the estimation errors were below 0.3302 °C.

3.3. Other state and parameter estimation with transfer learning

Battery model parameter estimation: The requirement of large amounts of data for battery modelling makes it difficult for conventional data-driven methods to build an accurate battery state estimation model. In addition, various battery types and packing structures in EVs have different external characteristics in different health states and working conditions [66]. The strong dependence of the model on the training data makes data-driven methods lose the generalization ability. The advanced applications of TL in battery modelling and parameter estimation also show significant performance in solving the aforementioned challenges. Fig. 8 illustrates a representative case for the parameter estimation of the battery pack model [67]. Here the main work aimed to improve model accuracy, which mainly refers to the accuracy of voltage estimation, with a small volume of data collected from different electrical buses. Specifically, the operation data and health perceptive information are adopted for unsupervised feature extraction with the data collected from 50 A-type buses by using a restricted Boltzmann machine (RBM). Then, the trained RBM was transferred to the modelling process of B-type buses. The regression layers are added to form the feed-forward NN for establishing the supervised learning of voltage estimation by using a tiny dataset from 3 B-type buses. The voltage estimation results shown in Fig. 8 [67] indicated a significant accuracy increment (about 47.7%) in comparison with the methods without TL. In Ref. [68], fine-tuning-based TL was also adopted to identify the parameters of the physics-based fractional-order model (FOM). A back propagation (BP) NN was designed to identify the time constants of the FOM, where the measured battery impedance was treated as the input of the BPNN. By fine-tuning the output layer of a pre-trained BPNN established from the data of fresh cells, the target BPNN was able to identify the time constants of aged cells.

Curve reconstruction or prediction: In real applications, the voltage curve prediction of both charging and discharging processes by using just a few data could also significantly support battery state estimation and health prognostic. Here the battery ageing will cause variations in charge and discharge curves, while different battery types also present different curve shapes, which become the main challenges for the conventional data-driven methods. In this context, TL has been also adopted for the prediction of battery voltage curves. For example, CNN is used in Ref. [69] to predict a battery charging voltage curve based on only 30 known points collected within 10 min. The pre-trained CNN model can be transferred to different batteries operating under various conditions with little data for retraining, and satisfactory prediction results could be obtained. In addition, an autoencoder and decoder was adopted in Ref. [70] to predict the discharge voltage curve. The early discharge data were used to fine-tune the model to predict the following whole discharge curve.

4. Transfer learning-based battery ageing prognostics

In general, ageing mechanisms are influenced by many external factors, such as temperature, humidity, depth of discharge (DoD), mean SoC, current rates, etc. The main ageing mechanism categories and the severity of side reactions differ under various operating conditions. For example, the growth of the SEI layer is the main ageing mechanism at room and high temperatures, while lithium plating dominates battery ageing at low temperatures. Furthermore, batteries with various chemistry and formats also show different degradation patterns. The discrepancy between domains caused by the above factors makes the data-driven SoH estimation or lifetime prediction models poorly generalisable. In real applications, batteries generally operate under various but not full DoDs with dynamic current profiles and the sampling frequency of the battery system is usually low. In this context, it is difficult to obtain enough labelled data for battery degradation modelling in real applications. Different from those general challenges in state estimation, the challenges in predicting battery ageing arise primarily from the different mechanisms of battery ageing that occur under different working conditions and the limited labelled real capacities for model development. In data-driven battery ageing prognostic, TL is the effective way to address the challenges above, which are reviewed in detail in the following sections. The TL in battery ageing prognostic could be illustrated in Fig. 9.

4.1. SoH estimation with transfer learning

Data-driven battery SoH estimation can be divided into feature-based and feature-free methods, which differ based on the criterion of whether manual feature extraction is required. Machine learning or deep learning is required to train the model by inputting the extracted features or the raw data. However, the hidden features learned by the data-driven methods vary for various batteries with different ageing conditions, making the conventional data-driven methods present poor generalisation. Some specific challenges for SoH estimation of batteries are summarised below:

(1) **Feature extraction**. Either the manually extracted features or the automatically extracted features are sensitive to the training data of current, voltage, temperature, and time. When the battery current loads change, its voltage and temperature values also change, so the extracted features differ. For example, as the battery current increases, the voltage slope becomes larger when charging at constant

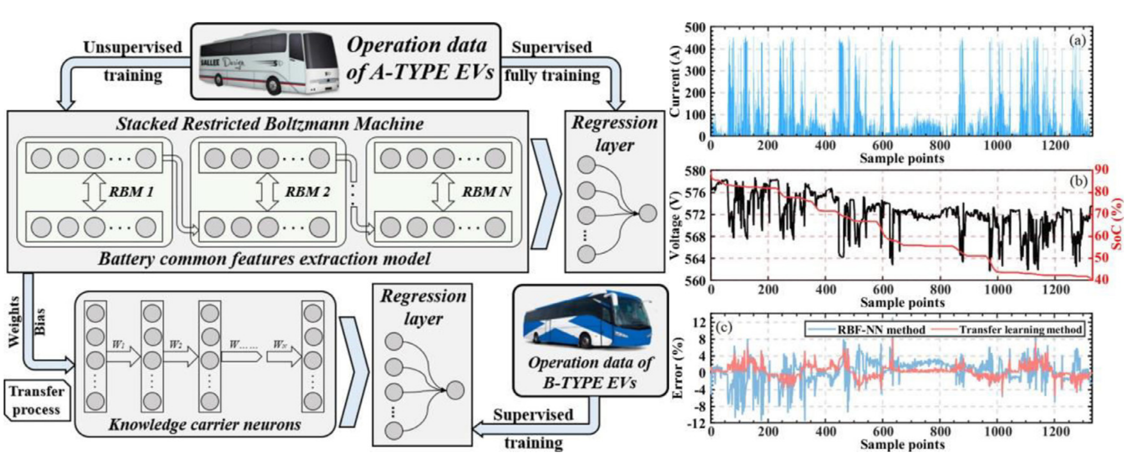

Fig. 8. Representative case for battery parameter estimation in EVs based on TL [67].

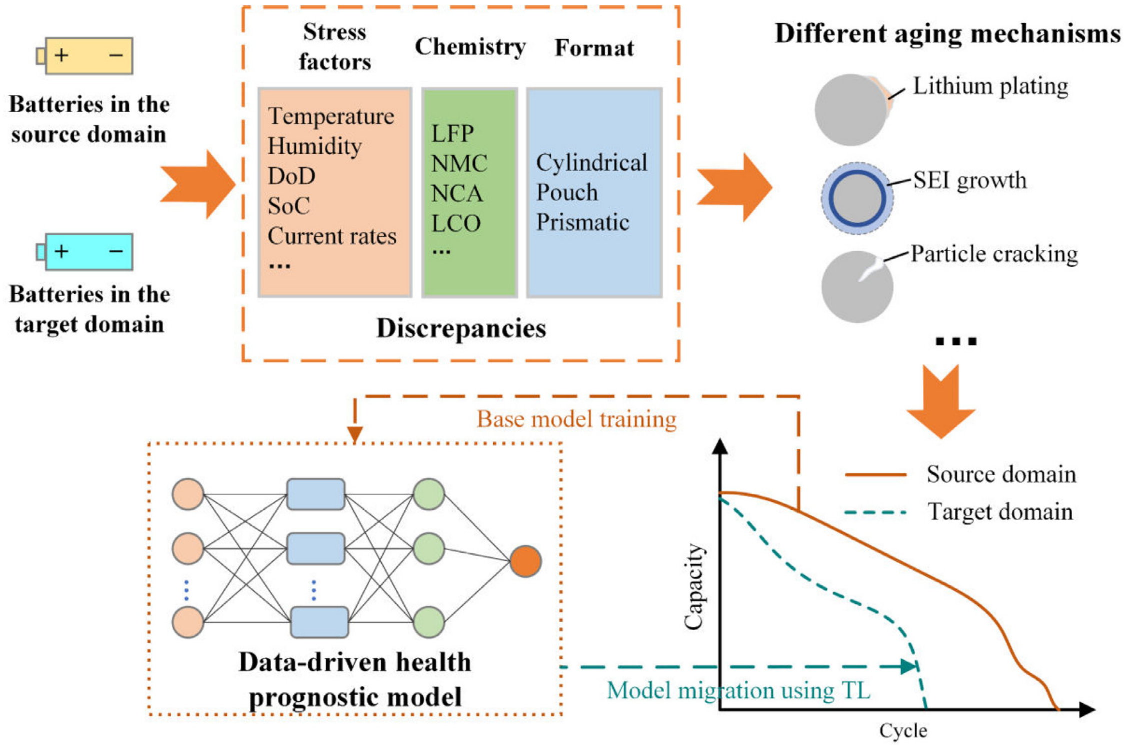

Fig. 9. The TL in battery ageing prognostic.

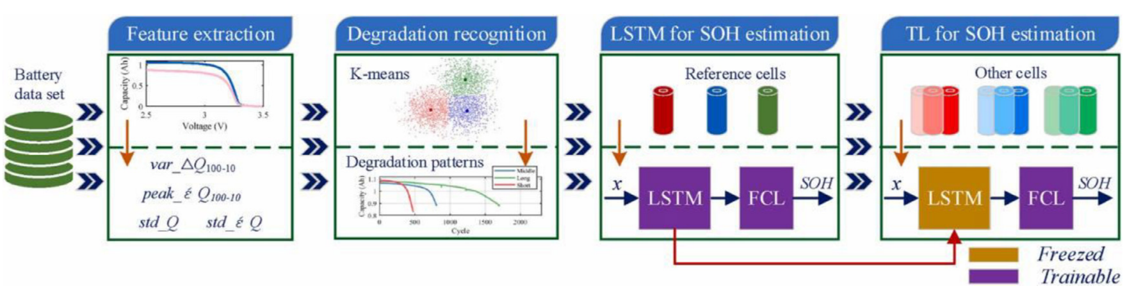

Fig. 10. Framework for fine-tuning-based battery SoH estimation [71].

currents, further making the features such as the time interval during equal voltage interval reduce. In this context, different current loads will make the extracted HIs present a large domain discrepancy.

(2) **Different usage patterns**. Battery DoD will vary for different application scenarios. Therefore, even if the same current load is applied, there are discrepancies in the features caused by the different DoD for the extraction of the ageing features. In this case, the features extracted from different DoDs have different correlations with the battery capacities, so the trained data-driven model performs poorly when applied to battery SoH estimation with different DoDs.

(3) **Numerous external stress factors**. Various environmental stresses, such as temperatures, vibration cause the battery to age under different main mechanisms and change its voltage behaviour as described above. Therefore, the relationship between the input features and battery SoH would become different under various external conditions, making it difficult to apply the model trained under one condition to the SoH estimation under other conditions.

(4) **Lack of labelled data**. For supervised learning, labelled data are required to support the training process. However, in real battery applications, it is not common to go through the entire discharging cycle, resulting in reduced labelled data. Therefore, very limited information about the target batteries can be used to improve the model accuracy in real applications. However, the domain discrepancy caused by the above scenarios makes the trained model in the source domain fail to present satisfactory performance in the target domain.

Overall, the challenges in data-driven battery SoH estimation arise from the discrepancy between the domains and the limited labelled data for model training. Solutions for these challenges are conducted by TL in recent works, which can be divided into model parameter fine-tuning and domain adaptive strategies. The detailed state of the art for each solution is summarised below.

Model fine-tuning: The fine-tuning strategy is a popular way to retrain the model in TL-based battery SoH estimation. Fig. 10 illustrates a representative work [71]. The data from the source battery is used for pre-training whose parameters are transferred to the target battery and fine-tuned in the target domain. Another work used LSTM structure with adjustable fully connected layers for battery SoH estimation [72]. The NN for the SoH estimation model consisted of one LSTM layer and two fully connected layers. The LSTM layer was frozen after pre-training while the fully connected layers were adjustable to learn the new mapping relationship under new scenarios. According to the feature expression scoring (FES) rule, the fully linked layer was fine-tuned if the FES value was greater than a threshold, otherwise the fully connected layer was reconstructed in the TL process. Only 25% of the data was used for

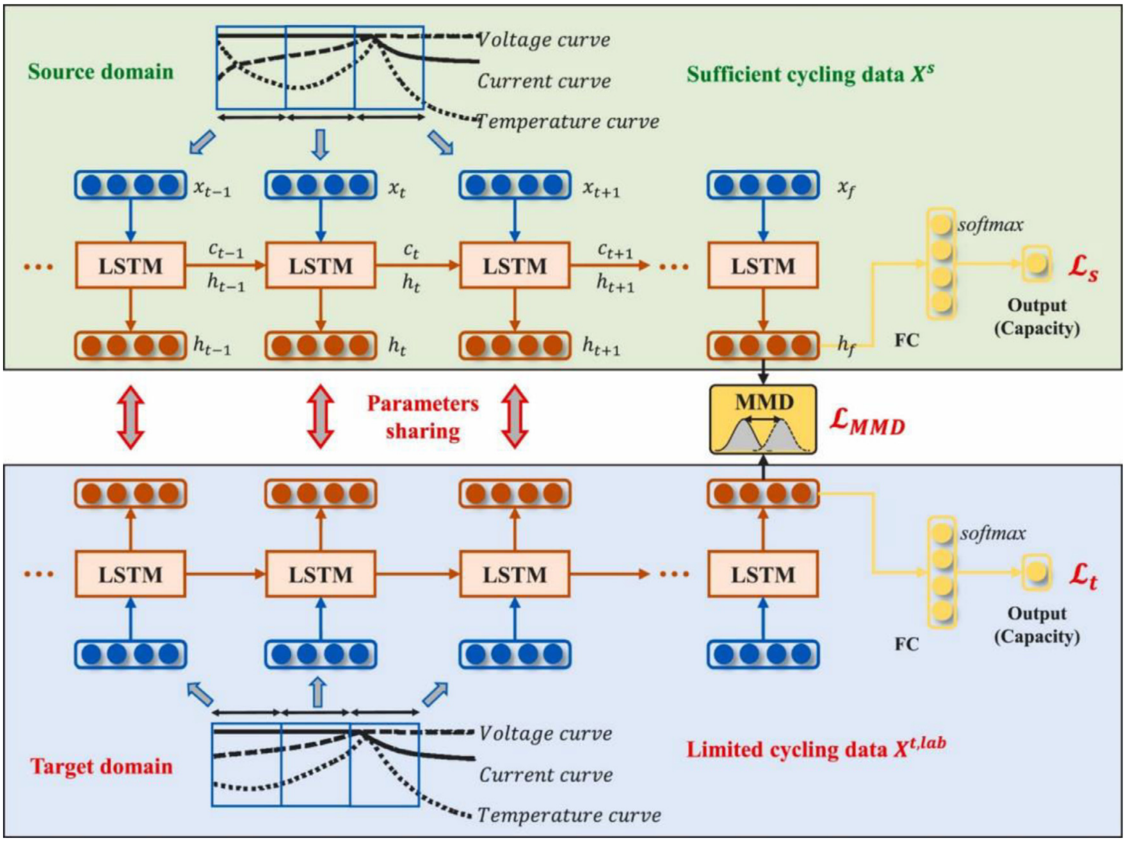

Fig. 11. Domain adaptative NN for battery SoH estimation [80].

TL, and the root mean square error (RMSE) of the estimations was less than 0.8%. With LSTM, Che et al. [73] and Deng et al. [71] integrated pattern recognization and transfer learning with a fine-tuning strategy to improve the model performance on the target domain. There are many other works that use the fine-tuning strategy to improve battery SoH estimation. For example, Li et al. [74] adopted the 2D CNN for the model training and fine-tuned the pre-trained model using small data from the target domain for the SoH estimation. The time-series data of voltage, current, and charge capacity were used to form the image formats for the 2D CNN modelling. Then, some specific layers (the third CNN and the following fully connected layers) were re-trained in the target domain, which reduced the estimation error by 22.52% compared to that without fine-tuning. In Ref. [75] several sub-networks constructed by the CNN framework were pre-trained by the source data set. Then the pre-trained parameters were transferred to the target domain and fine-tuned by using some of the target data. Finally, ensemble learning was used to fuse several weak estimations to obtain the final SoH estimation. Similarly, the fine-tuning strategy was used to retrain the fully connected layers of three subnetworks in [76] to provide a fused output for the battery pack SoH estimation under different ageing profiles and ageing conditions. Another work that tried to estimate the SoH of the battery packs was from Ref. [77], where the fine-tuning strategy was conducted on the cell mean model and cell difference model for the connected battery SoH estimation.

Domain adaptation: Two ways are implemented in domain adaptation for battery SoH estimation. One is to ensure that the manually extracted features have a small discrepancy. For example, Li et al. [78] adopted the transfer component analysis (TCA) for dimensional reduction. Different from the principal component analysis, TCA considers the MMD between the source domain and target domain and tries to reduce the difference in the reproduced kernel Hilbert space. Therefore, the domain discrepancy between the source domain and target domain of the final features was reduced, thus the accuracy of SoH estimation can also be improved. The TCA technology was also adopted by Jia et al. [79] for the common feature extraction in both source and target domains. Then, the extreme machine learning framework was used to estimate the SoH. Similar to the SoC estimation, another way of domain adaptation-based TL is to add the MMD in the loss function during model training to reduce the discrepancy between the source domain and target domain. For one representative case study demonstration, Han et al. [80] proposed a framework that used domain adaptative LSTM for the end-to-end battery capacity estimation, which is illustrated in Fig. 11. The charging data including current, voltage, and temperature were normalized to form the input of the LSTM layer. Sufficient source data (4 batteries) and limited target data (1 battery) were used for model training, which has two separate mean square error losses (L_s and L_t in Fig. 11). Besides, the MMD between the fully connected layer of the source domain and target domain was also considered as a loss (L_{MMD}) in the final loss function. Therefore, these three losses were reduced together in the training process to fit the mapping relationship between the input data and output capacity while reducing the domain discrepancy between the source domain and target domain. The results indicated that the proposed domain adaptative LSTM had better performance on battery SoH estimation than basic LSTM and LSTM with a fine-tuning method. MMD for domain adaptative NN was also used in other works. In Ref. [81] the MMD loss was integrated with the CNN framework to estimate the battery SoH. The data of the first 100 cycles was used for the domain adaptative CNN training while the rest was used for validation. In addition, the MMD with GRU-recurrent neural network (RNN) was proposed in Ref. [82] to reduce the domain discrepancy for battery SoH estimation. The generative adversarial learning was then added to provide the domain-invariant features. Besides the domain discrepancy between the source and target domain, domain distributions also show differences among multi-sources due to the different ageing conditions. Therefore, the authors in [83] proposed a multi-source domain adaptation network (MSDAN) based TL framework to predict the

Table 3
Summary of the main works in TL-based battery SoH estimation.

Refs.	Features	Base model	Transfer strategy	RMSE
Ref. [72]	• Initial charge voltage • Charge time at a certain voltage • Power of certain voltage interval	LSTM	Fine-tuning	≤1.04%
Ref. [73]	• Standard deviation, first principal component, entropy of the Q and dQ sequence	LSTM	Fine-tuning	≤0.78%
Ref. [71]	• Standard deviation of the Q sequence	LSTM	Fine-tuning	≤0.94%
Ref. [74]	• I, V, Q	2D CNN	Fine-tuning	≤ 0.0134 Ah
Ref. [75]	• I, V, Q segments	DCNN	Fine-tuning	≤2.5%
Ref. [76]	• Standard deviation of Q and dQ sequence are the basic features • Characteristic value, standard deviation, distribution range, principal component, entropy	LSTM, DNN, CNN	Fine-tuning	≤0.88% for CC ≤1.4% for dynamic
Ref. [77]	• Time duration in a certain voltage range	LSTM	Fine-tuning	≤0.42%
Ref. [78]	• Ratio of CC mode • Time duration in a certain voltage range • IC peak • Sample entropy of voltage curve	Kernel ridge regression model	Domain adaptation	≤2.5%
Ref. [79]	• Voltage values at a certain ratio during the charging process	BPNN	Domain adaptation	≤2.84%
Ref. [80]	• I, V, T	LSTM	Domain adaptation	≤2.79%
Ref. [81]	• Voltage curve	2D CNN	Domain adaptation	≤1.263%
Ref. [82]	• I, V, T, time	BiGRU	Domain adaptation	≤2.15%
Ref. [83]	• I, V, T • Generated HI	BiGRU	Domain adaptation	≤0.105 for HI

ageing of batteries. The MMD is added to reduce the domain discrepancy of the generated HIs between the target domain and each source domain.

Table 3 summarizes some typical TL-based SoH estimation applications, where the extracted HIs or the raw data, the base model for transfer, the transfer strategy, and the accuracy (represented by the RMSE of the estimations) are included. In summary, all the TL-based estimation accuracy has been improved in comparison with the conventional data-driven model. It also shows that the fine-tuning strategy generally presents better accuracy than the domain adaptation one, while sufficient labelled data are required to retrain the model. LSTM, GRU, and CNN are the most popular base models to build the SoH estimation model either with manually extracted HIs or the raw data.

4.2. Future ageing trajectory and lifetime prediction with transfer learning

In addition to the SoH estimation, ageing trajectory and lifetime prediction also have vital importance in battery health prognostic. The different external stresses and initial manufactory inconsistency lead to different ageing trajectories, which cause the different distributions of degradation curves. The challenges faced by conventional data-driven ageing trajectory and lifetime prediction are quite similar to that in SoH estimation because they all arise from the same problem but with different goals. Therefore, in this section, the specific challenges are not listed in detail.

Conventional data-driven predictions of battery ageing trajectory and lifetime are typically achieved by mapping the running cycles and capacity or by modelling the sequence variation relationships. However, different degradation patterns and battery lifespan cause the data-driven model trained by the source domain to fail to meet the requirement of prediction in the target domain. In other words, it is difficult for conventional data-driven methods to tackle the domain discrepancy manifested by different ageing trajectories. In addition, most conventional methods need real capacity for the modelling, which is difficult or impractical to obtain in the real world. In recent years, the development of TL in battery ageing trajectory and lifetime prediction has shown great effectiveness to address the above challenges.

The most widely used method is to integrate the model retraining with NNs. For example, Tang et al. [84] proposed a feed-forward NN-based model with the TL concept to predict battery future ageing trajectory. Here a base model is first built from an accelerated ageing dataset to capture battery capacity degradation with time. After formulating an input-output slope and bias correction structure, the established base model is transferred to predict the ageing trajectory of the target cell. In Ref. [85], to improve battery ageing trajectory prediction performance considering the local capacity fluctuations, a particle filter-based method with the TL concept was designed by involving a gradient corrector for each particle. Furthermore, to generate enough high-quality battery ageing trajectory datasets, a TL-based data-driven method is proposed in [86], as illustrated in Fig. 12. Specifically, a multi-layer NN was utilised to map the key HIs to the ageing status, and the established network was then transferred to different ageing scenarios via piece-wise linear migration technique. The generated ageing trajectory dataset exhibits an ultra-low error of only 1%.

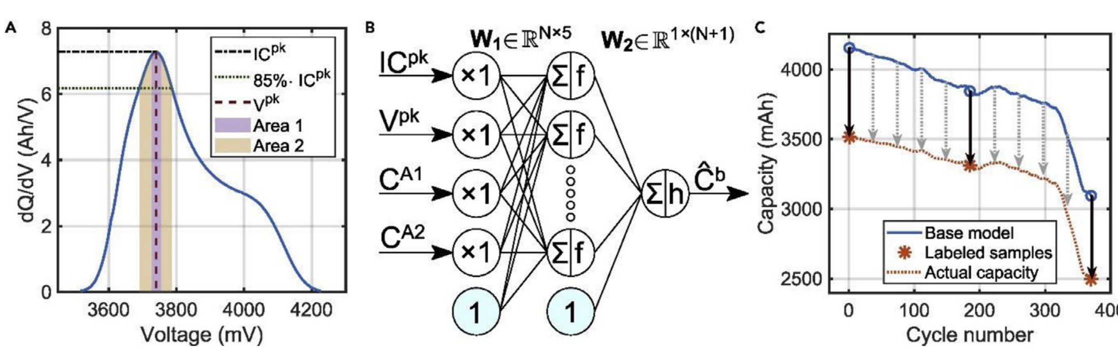

Fig. 12. TL-based data-driven method for the generation of high-quality battery ageing trajectory datasets [86].

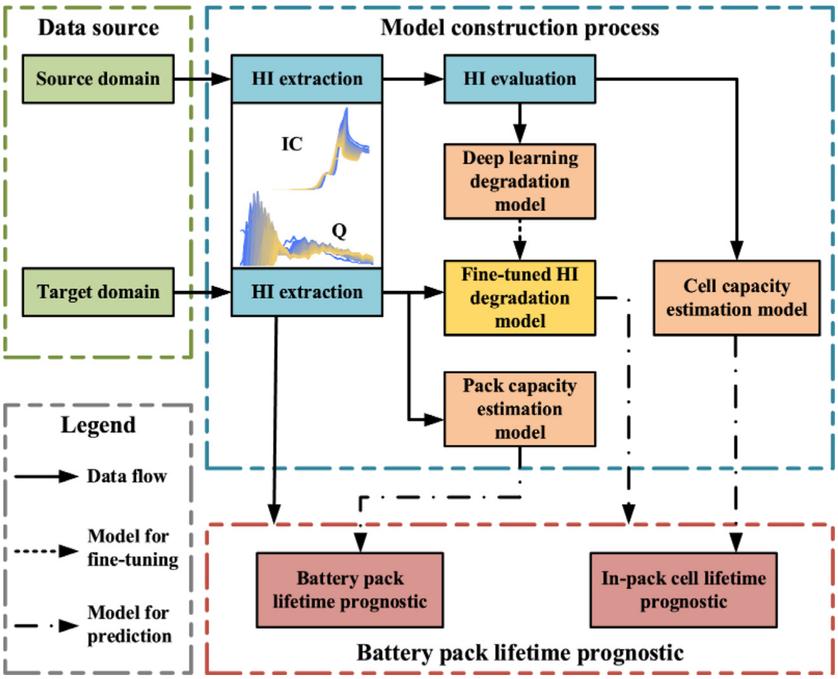

Fig. 13. Fine-tuning strategy-based trajectory prediction for battery packs [89].

RNN is proven to have a good performance on battery ageing trajectory and lifetime prediction due to the sequence variation nature of the battery. The TL with RNN and LSTM is a proper way to improve prediction accuracy. For example, Kim et al. [87] applied LSTM to encode the general information in the source domain and keep such information in the target domain by freezing the LSTM layer. The fully connected layer, which was sensitive to the specific battery types, was retrained and fine-tuned to improve the prediction accuracy. The results illustrated that the predicted errors have been improved by more than 20% by the TL strategy, with less than 20% data for model retraining. However, the actual capacity is hard to be obtained in real applications. Therefore, the future degradation of HIs was trained by the RNN structure. Then, the fine-tuning strategy was used to retrain the HI degradation prediction model for the future degradation trajectory prediction in Ref. [88]. A cell-to-pack prediction framework with the fine-tuning strategy for the battery pack trajectory prediction was proposed in Ref. [89], which is shown in Fig. 13. The HI degradation model was trained by the LSTM using the data from the separated battery cell. Then the fully connected layer was fine-tuned by using the HI extracted from each connected battery cell during the early cycles. Finally, the future HI values were predicted to support the future SoH predictions. The results indicated that both the trajectory of the battery pack and the trajectory distribution of the connected battery cells were predicted accurately with an error of fewer than 25 cycles with only the first 50 cycles for fine-tuning. For battery storage ageing conditions, a transferred RNN-based framework was proposed in [90] to achieve reliable future ageing trajectory predictions of calendar capacity under both witnessed and unwitnessed cases. The transferred framework consisted of a base model part and a transfer part. Here the base model was first built by adopting a time-saving dataset from high storage temperatures and SoCs, while the transfer part would be adjusted by utilizing only a small portion of capacity data from unwitnessed cases. Based upon this TL solution, the framework was able to provide satisfactory predictions of calendar capacity ageing trajectory under three different storage SoC and temperature conditions. The results showed that with only 20% of the data for fine-tuning, a satisfactory prediction can be achieved with R^2 over 0.97. The limited labelled data is one challenge for TL based lifetime prediction. In Ref. [91], a semi-supervised based prediction was proposed, where only the data from one battery is used for the reference modelling, and sparsely limited labelled data were used for the fine-tuning. The battery dataset consisting of 45 cells with different running cycles were used for the verification, which achieved a mean error less than 23 cycles with only 3 labelled data used.

Apart from NN, TL has been also adopted in other machine learning techniques, especially for kernel-based data-driven models to predict battery ageing trajectory. For example, to consider the effect of knee point on battery ageing, a TL-based GPR method was designed in [92] to predict the battery's future two-stage ageing trajectory. Here a base model was first trained offline by using the easily-collected accelerated ageing data. Then a migrated mean function with the TL concept was designed and equipped with the GPR framework. Through coupling the TL element into GPR, the future two-stage ageing trajectory can be successfully and accurately predicted by using only a few starting ageing data (first 30%), paving the way to significantly decrease the experimental effort.

5. Challenges and future trends

To widen the TL-based technology for battery management, this section first discusses the key challenges of the existing TL-based solutions in the field of battery management. Afterwards, the potential promising trends to boost the development of more efficient TL-based battery management methods are given.

5.1. Key challenges

Although considerable progress has been made in the field of TL-based battery management in recent years, the existing studies are still at an early stage. The performance of the TL is influenced by the data availability in a battery system, the reference data for base model training, and the label of the data in both the source and the target domain. Furthermore, there also exists a verification issue about the TL-based model in real-world applications if the labelled data is lacking. Considering these aspects, the main challenges faced by TL-based battery management can be summarized into two categories, which arise from the limitations of TL-based algorithms and the implementation bottlenecks. According to the summary of the current state-of-the-art in TL-based battery state estimation and ageing prognostics, two main categories of methods are widely used, namely parameter fine-tuning and domain adaptation. The main advantages and drawbacks of these methods are

Table 4
Summary of the main advantages and deficiencies of different TL methods in battery management.

Methods	Main advantages	Deficiencies
Model-parameter fine-tuning	• Easy to implement • Fast calculation • Suitable for different application scenarios	• Suffer from underfitting or overfitting • Require sufficient labelled data from the target domain • Lack of interpretability
Domain adaptation	• Domain discrepancy is reduced • Interpretable • Unlabelled data can be used	• Increased computational burden • Slow down the training convergence with additional loss • Sensitive to the transfer loss

listed in Table 4, while the detailed key challenges are summarized below.

Limitations of TL model itself. The TL model itself has some limitations in its implementation. For fine-tuning strategy in NN, as only a small amount of labelled data in the target domain will be used during the re-training process, overfitting or underfitting is likely to occur, especially when there exist a large number of NN parameters that need to be fine-tuned. Such a situation is common in battery ageing prognostic, as the real value of battery capacity can only be determined at each maintenance, which occurs occasionally throughout the whole battery lifespan, resulting in little labelled data in the target domain. In this context, the fine-tuning process needs to be carried out meticulously to ensure both accuracy and generalization of the re-trained NN model. For the domain adaptation strategy, it is more complex than the fine-tuning strategy and might suffer from huge computational effort. For example, MMD in a deep NN can significantly increase the computational complexity, especially when the size of the NN (i.e., the number of hidden layers and neurons) and the unlabelled data increase. The increased computational complexity caused by domain adaptation limits the online implementation of TL. For the kernel reconstruction-based TL, as kernel function usually has a fixed structure to tune, how to well equip TL element into the model or how to design a proper TL way considering battery dynamics will highly affect the TL performance of the kernel-based model. The aforementioned limitations will bring challenges to the accuracy, generalization ability and online implementations of TL.

Difficulties in real applications. The data acquisition ability of real BMS is another important issue that affects the performance of TL. The biggest challenge to TL in real-world applications is the lack of labelled data, which arises primarily from low sampling frequency. For instance, the 10-s sampling period in real operations of electric vehicles makes it difficult to capture some important information between two adjacent sample points, which leads to the reduced accuracy in data-driven model. In battery ageing prognostics, there will be only a few labelled data about battery real capacity in the whole life cycle due to infrequent maintenance, significantly increasing the difficulty of predicting the ageing trajectory when applying TL. Furthermore, the difficulty in obtaining labelled data for online implementation of TL can also be caused by some technical challenges. Take SoT estimation as an example, collecting data of battery internal temperature is challenging since it is costly and impractical to insert a temperature sensor in each cell of battery pack to obtain the internal temperature information without producing damage to the cell. In addition, the reference data for base model training will also affect performance of TL during real-world implementations. In order to achieve accurate estimations and prognostics, the features and their distributions of the source and the target batteries must be similar, which also brings challenges to the selection of the reference data. Hence, the data used for base model training should be selected carefully to guarantee the performance of TL. Apart from the data acquisition issue, the lack of key battery mechanisms in the predictions using TL is another limitation. Existing TL-based estimation and health prognostics rely on pure data-driven algorithms, which cannot provide reliable and reasonable results in some cases. Finally, the TL algorithms also suffer from the verification issues in real applications, which stem from the lack of labelled data in the target domain, making it difficult to evaluate the effectiveness of TL strategies in the target domain. For instance, under real-world scenarios of battery ageing prognostics, the battery real capacity between two maintenances can never be known. Even with a few labelled data obtained from maintenances for TL implementation, the performance of the final TL model cannot be verified.

5.2. Future trends

To further improve the performance of TL-based battery state estimation and ageing prognostic methods, and to popularise the TL-based methods in the battery management field, some aspects are recommended to be further considered in future research, as shown in Fig. 14.

Smart sensors for obtaining more transferable information: A key step to achieving efficient TL-based battery state estimation and ageing prognostic is to collect suitable data that contains valuable information for the development of TL-based data-driven models. To achieve this, numerous sensors such as current sensors, voltage sensors, and temperature sensors have been widely utilized. Although useful information can be obtained from these sensors, lots of other information such as battery expansion, pressure, and strain are still difficult to be captured. To obtain more useful information for TL-based method development in the battery management domain, advanced and smart sensor technology are worthy of being developed. In this context, more battery external and internal information can be obtained to benefit the TL applications of both battery state estimation and ageing prognostics by providing more features and labelled data for TL implementations. In this way, the transferred data-driven models are less prone to overfitting or underfitting, and their generalization ability could be greatly improved with the increase of labelled data in the target domain.

Knowledge-motivated TL: Current research is mainly focused on incorporating TL elements into the pure data-driven models to meet the various requirements of battery management applications. Although many benefits have been achieved in the fields of battery state estimation and ageing prognostics, there are still significant limitations to pure data-driven-based TL methods, particularly caused by the lack of battery knowledge or mechanism information to understand the predictions or transferred results. Besides, although pure TL-based data-driven methods can help the users reduce the experimental effort required to generate available training data, enough data that contains sufficient battery estimation or ageing information are still required to ensure that a pure TL-based data-driven model can be trained well. In this context, it makes sense to further enhance the performance of TL-based data-driven methods by involving additional elements. A promising future trend is the development of knowledge-motivated TL methods by combining battery mechanism or management knowledge into the TL-based data-driven methods. In this way, TL-based data-driven models can incorporate battery knowledge that helps them make reasonable predictions and better understand the underlying TL mechanism for both battery state estimation and ageing prognostics. Consequently, the results yielded by knowledge-motivated TL will not deviate from the underlying battery mechanism so that the TL-based data-driven models can become more reliable. This can also help to reduce the data amount required for model training, which in turn benefits the further reduction of experimental effort.

Self-adjusted TL: The general logic of current TL-based data-driven methods in the battery management field contains two parts: a base model part needs to be first trained to contain information from the

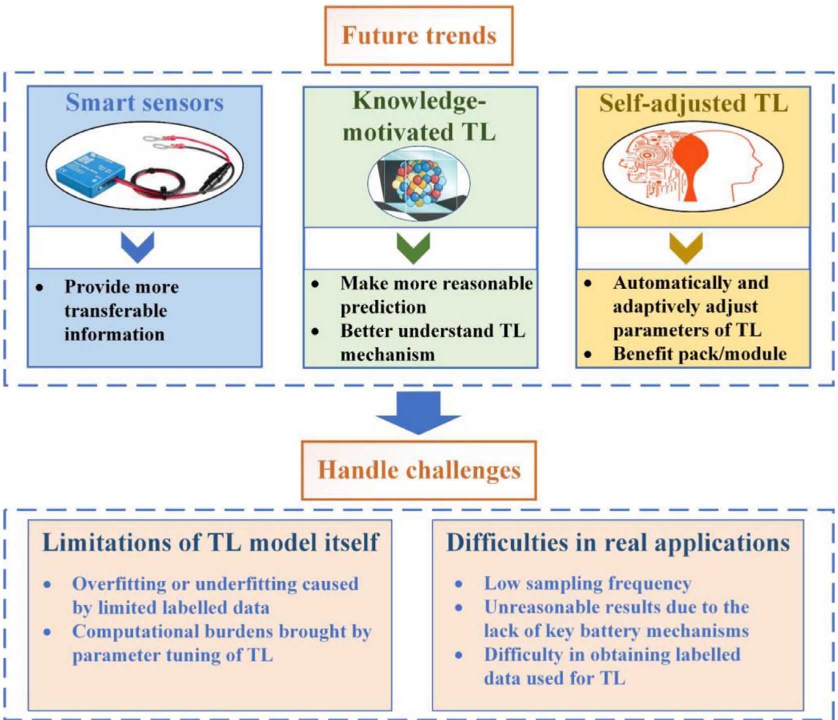

Fig. 14. Some aspects of future trends in TL-based battery management.

general application, while a transfer part to provide a suitable transfer way so that the information from the base model part can be effectively adopted under the conditions that are different from the base model. In general, the parameters in the transfer part are tuned one by one for different battery cases, which would cause huge computational effort and be inconvenient for battery state estimation and ageing prognostics, especially at the pack or module level where tens or hundreds of battery cells are connected in series or parallel. In this context, to popularise the TL-based data-driven methods in the pack or module level-based battery management, self-adjusted TL technologies are worthy of being explored in the future to adjust the corresponding parameters of the transfer part automatically and adaptively so that the computational burdens and the complexity of transferring process can be greatly reduced. In this way, TL-based technology will become more popularized to benefit more energy or transport applications such as grid energy storage, electric vehicles, and electrical aircraft that contain hundreds to thousands of battery cells.

6. Conclusion

Technologies to accelerate the delivery of reliable battery-based energy systems are critical to the popularisation of clean transport, and of strategic importance for the world to achieve clean growth and net zero carbon target. To improve the performance of data-driven strategies in battery management, transfer learning technology becomes a promising approach and is being adopted in more and more areas of battery management. This paper provides a systematic review of transfer learning-based solutions in battery management for the first time, with the focus on recent challenges and future opportunities. The scientific literature on two popular research topics including battery state estimation and ageing prognostics are discussed, while the associated data-driven limitations, the benefits and applications of transfer learning methods are thoroughly explored and analyzed. Afterwards, the key challenges and future trends are discussed, aiming to encourage more researchers to contribute improved technologies for expanding transfer learning-based applications in the field of battery management. In summary, with the rapid development of artificial intelligence and data science engineering, advanced transfer learning-based approaches with high performance and strong generalization are highly required to promote the smarter management of battery, while lots of corresponding strategies are still in their infancy and need to be improved. The authors hope that this review will provide insights into the operation, research, and design of more effective and robust transfer learning-based technologies for battery state estimation and ageing prognostics. This will further advance the development of smarter battery management solutions, while delivering significant benefits to sustainable and clean energy transitions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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