ARTICLE IN PRESS

Journal of Manufacturing Systems xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Efficient stochastic parametric estimation for lithium-ion battery performance degradation tracking and prognosis ☆

Lakmali Nadeesha Kumari [a], Peng Wang [a,b,*]

[a] Department of Electrical and Computer Engineering, University of Kentucky, Lexington 40509, USA
[b] Department of Mechanical and Aerospace Engineering, University of Kentucky, Lexington 40509, USA

ARTICLE INFO

Keywords:
Battery health prognosis
Parametric estimation
Bayesian inference
Conditional invertible neural network

ABSTRACT

Because of lithium-ion batteries' wide applications in our daily life and industrial sectors, understanding their performance degradation mechanisms and improving their health management are essential to improve their durability, reliability, and sustainability. However, Li-ion batteries exhibit complex performance degradation behaviors, typically in a combination of nonlinear gradual degradation with time-varying deterioration rates and abrupt performance changes (e.g., sudden capacity drops or regenerations), posing significant challenges to accurate and reliable degradation tracking and prediction. This study tackles this challenge from two perspectives: an advanced stochastic model to describe complex degradation patterns and a generalizable Bayesian inference neural network for efficient parametric estimation of the stochastic model. Specifically, the stochastic model employs a rational polynomial term for tracking gradual battery degradation and a compound Poisson process term for capturing abrupt capacity changes. To estimate the model parameters related to degradation rates and scaling, a novel Conditional Invertible Neural Network (CINN) architecture is investigated. CINN can comprehensively evaluate the degradation likelihood (i.e., dependencies of capability observations on various battery degradation patterns) by leveraging extensive simulation data during the training phase, and then through its unique inverse calculation capability, efficiently and probabilistically estimate the posterior density of model parameters conditional on capacity observations in the real-world applications. The effectiveness of the proposed stochastic model and parametric estimation method, in terms of accuracy and generalizability, has been evaluated using simulation data and run-to-failure tests provided in NASA's lithium-ion battery dataset. Experimental studies and comparisons reveal that the CINN-based parametric estimation substantially outperforms two commonly adopted Bayesian inference methods, Particle Filtering (PF)-based step-by-step estimation and Markov Chain Monte Carlo (MCMC)-based batch estimation, on both accuracy and computational efficiency.

1. Introduction

Because of advantageous properties in power capacity, thermal stability, and other factors, lithium-ion (Li-ion) batteries have been widely applied in our daily life and industrial applications [1]. For example, in manufacturing, Li-ion batteries equipped electric freight vehicle fleets [2] and automated guided vehicles (AGV) greatly enhance the manufacturing automation, flexibility, and efficiency toward smart manufacturing [3,4].

As Li-ion batteries become more integral to industrial equipment, their performance directly affects overall system reliability, highlighting the importance of battery condition monitoring and health management [5]. Presently, battery health management typically relies on conventional condition-based maintenance, which involves routine checks and replacements at predetermined intervals. However, the shift toward predictive maintenance, which schedules maintenance based on dynamic battery condition assessments and Remaining Useful Life (RUL) predictions, can minimize unnecessary maintenance and equipment downtime. This approach has the potential to reduce maintenance expenses and enhance production efficiency [6,7].

Predictive maintenance relies on two core components: performance degradation tracking and RUL prediction [8]. Performance degradation

☆ 52nd SME North American Manufacturing Research Conference (NAMRC 52,2024)

* Corresponding author at: Department of Electrical and Computer Engineering, University of Kentucky, Lexington 40509, USA.
E-mail address: Edward.Wang@uky.edu (P. Wang).

https://doi.org/10.1016/j.jmsy.2024.03.017
Received 31 March 2024; Accepted 31 March 2024
0278-6125/© 2024 The Society of Manufacturing Engineers. Published by Elsevier Ltd. All rights reserved.

Please cite this article as: Lakmali Nadeesha Kumari, Peng Wang, *Journal of Manufacturing Systems*, https://doi.org/10.1016/j.jmsy.2024.03.017

tracking models the dependencies of degradation on various influencing factors such as time, usage patterns, and environmental conditions, which are then leveraged to predict batteries' future degradation trajectories h and RUL [9]. Existing methods in performance degradation modeling can be categorized into three approaches: physics-based, data-driven and hybrid. Physics-based models empirically and mathematically represent degradation as a function of influence factors, and determine model coefficients from experimental data through deterministic regression techniques [10–12]. While generalizable to describe global degradation behaviors, these models fall short in capturing instance-to-instance variations or uncertainties [13]. Data-driven models, especially upon emerging machine learning techniques such as statistical regression [14], relevance vector machines [15], neural networks [16], and deep learning [17], aim to discover the degradation patterns from historical data in a black-box modeling nature. This approach, while usually achieving better estimation and prediction accuracies than physics-based models due to their ability to learn from large datasets, lacks the interpretability that is necessary to physically validate the decision-making process. The hybrid approach combines the strengths of the previous two approaches, i.e., integrating physics-informed model structures with a data-driven estimation algorithm, aiming to enhance the interpretability and generalizability of the modeling as well as the accuracy of estimations and predictions [18,19].

Our previous work has developed an advanced stochastic model that employs a rational polynomial term for tracking nonlinear gradual battery degradation and a compound Poisson process term for capturing abrupt capacity changes [20]. To estimate the model parameters that determine the degradation rates as well as probabilistically evaluate the variation of model parameters under different conditions, Bayesian inference techniques are investigated in estimating the posterior Probability Density Function (PDF) of model parameters on battery capacity observations. Two representative Bayesian inference techniques are compared: Particle Filtering (PF) as a sequential estimation method and Markov Chain Monte Carlo (MCMC) as a batch estimation method. PF applies sequential Monte Carlo sampling to estimate posterior PDFs of model states and parameters, and is applicable to nonlinear and non-gaussian system estimation because of its Jacobian-free calculations [20–22]. MCMC follows a similar Monte Carlo sampling approach. But instead of updating the parameter distribution after each step in the sequence of observations as is done in PF, the model performance in MCMC is evaluated across the whole training set of observations before changing the estimated parameters for a batch estimation [23,24]. Findings from [20] indicate that PF-based step-by-step estimation predicts future degradation based on the latest degradation trend and misses an overview of global degradation trend, especially related to non-stationary abrupt capacity changes. MCMC is better in adaptively capturing abrupt events, but involves more model parameters and falls short in computational efficiency.

In this paper, a novel Conditional Invertible Neural Network (CINN)-based posterior PDF estimation method is investigated for implementation of Bayesian inference and parametric estimation of the stochastic battery degradation model developed in [20]. CINN is unique for its affine coupling block structure and inverse calculation capability. During the training phase of the CINN, capacity observations and stochastic model parameters are prepared in pairs, and their conditional PDFs are mapped into unit Gaussian distributions to minimize correlation ambiguities between model parameters and capacity observations. Once the training is completed, the CINN applies its inverse calculation capability to estimate the posterior PDF upon capacity observations, through inverse mapping from sampling from unit Gaussian distributions. Compared to other Bayesian inference methods, there are two major advantages of this CINN method:

- CINN training can be realized using simulation data, which minimizes the real-world data collection/labeling efforts and also facilitates the model's ability to generalize across a wide range of battery degradation scenarios through comprehensive simulations;
- Unlike PF or MCMC that perform model training for individual batteries, the CINN approach allows for the direct input of capacity measurements to obtain stochastic model parameters through straightforward calculations. Hence, CINN is more versatile in its application, as it does not necessitate individualized training per battery, and surpasses computational efficiency.

To evaluate the performance of the combination of the advanced stochastic battery degradation model and CINN-based probabilities model parametric estimation method, experimental evaluations are done in the run-to-failure tests provided in the NASA's lithium-ion battery data. Comparative studies are also done between CINN and PF and MCMC. The following sections detail the methodologies, experimental studies, results, and findings.

2. Methodology

This section starts with the review of the advanced stochastic battery degradation model, and then introduces CINN-based posterior PDF estimation.

2.1. Stochastic battery degradation model

Developed in our previous work [20], the stochastic model can account for both non-linear gradual degradation and transient capacity changes in battery performance degradation. The model employs a rational polynomial model with two unknown parameters α and β to describe gradual capacity degradation:

$$x_k = x_{k-1} - \frac{\alpha\beta k}{10000 + (\beta k)^2} + v_p \tag{1}$$

where k denotes battery charging-discharging cycles, and the modeling uncertainty is characterized by v_p. The unknown parameters α and β control the degradation rate's vertical scaling, horizontal scaling, and peak position, respectively. Fig. 1.

Besides gradual degradation, batteries may experience abrupt capacity changes, for example transient capacity regeneration events that drastically raise capacity values after a long period of rest between two sequential charge-discharge cycles. The regeneration events arise as a continuous, random process with jumps, which could be detailed by Compound Poisson Process (CPP). The abrupt changes in capacity are modeled as stochastic increments:

$$\Delta C_r(k) = \sum_{i=1}^{\lambda k} R_i \tag{2}$$

where i^{th} event's regeneration magnitude is R_i, the event frequency is represented by λ. Regeneration magnitudes are not constant but can be characterized by different non-negative distributions, whereas regeneration frequency can be assumed to follow an exponential distribution and to be a constant value for a particular battery. To get a comprehensive stochastic degradation model, the rational polynomial model and the CPP model are combined as follows:

$$x_k = x_{k-1} - \frac{\alpha\beta k}{10000 + (\beta k)^2} + \delta\left((k)mod\left(\lambda^{-1}\right)\right)R_k + v_p \tag{3}$$

In this study, five different distributions are examined for R_k: gamma distribution $R_k \sim Gamma(s, \vartheta)$, normal distribution$R_k \sim N(\mu, \sigma)$, exponential distribution $R_k \sim \exp(m)$, uniform$R_k \sim U(a, b)$ and Chi-square: $R_k \sim \chi^2(\kappa)$, where s and ϑ determine the scale and shape of the gamma distribution, μ and σ are the mean and variance of the normal distribution, m determines how quickly the exponential distribution decays, a and b are the minimum and maximum values of the uniform

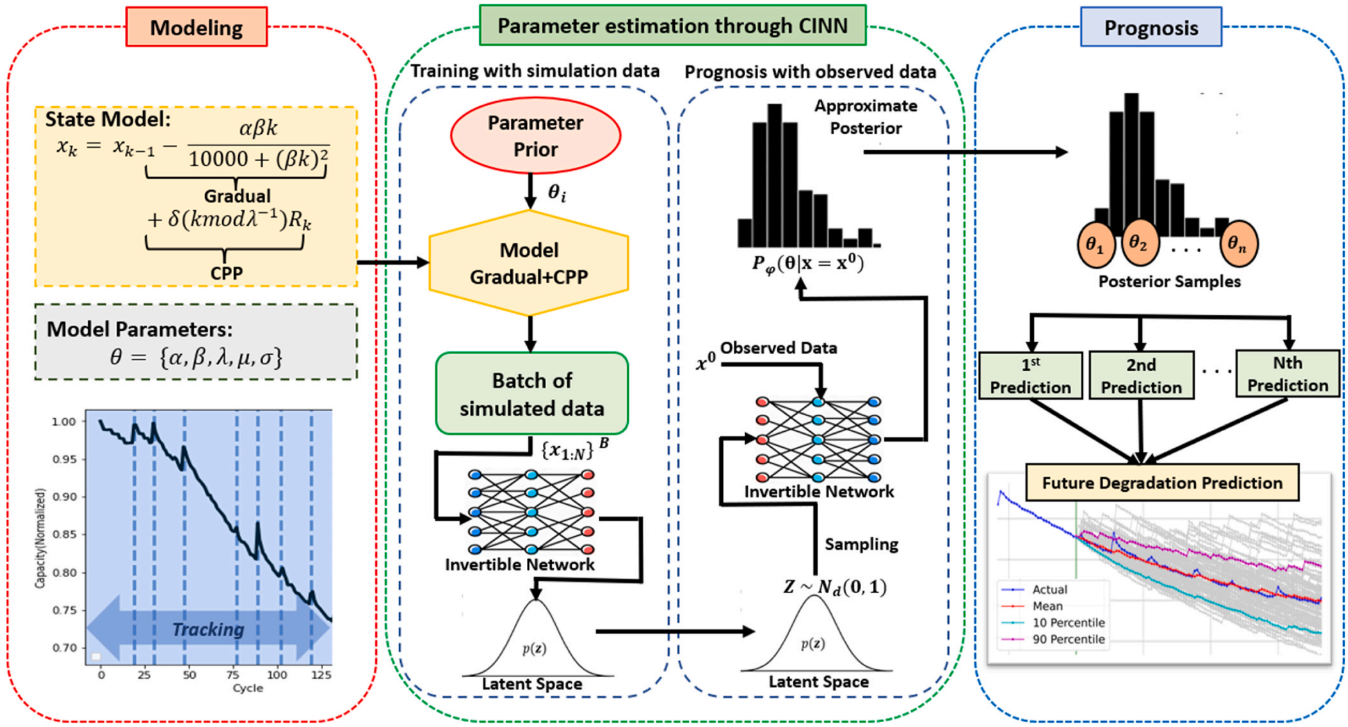

Fig. 1. Overview of the stochastic battery degradation model and CINN-based parametric estimation for battery performance tracking and prognosis.

distribution, and κ is the degree of freedom for the Chi-square distribution. Historical regeneration occurrences are used to fit the relevant distributional characteristics.

2.2. CINN-based posterior estimation

The objective of the probabilistic parametric estimation is to learn a posterior PDF $p(\boldsymbol{\theta}|x_{1:N})$ given the historical degradation development $x_{1:N}$. The parameters $\boldsymbol{\theta}$ refer to the unknown parameters in Eq. (3), for example α, β, λ, μ and σ if $\underline{R_k}$ is modelled as a normal distribution. One challenge for posterior PDF estimation is that there may not be a one-to-one mapping between $\boldsymbol{\theta}$ and $x_{1:N}$. Hence, estimating $p(\boldsymbol{\theta}|x_{1:N})$ is indeed an ambiguous inverse estimation problem. One way to address this problem is to introduce an additional latent variable $\mathbf{z}$, to constrain the mapping in the inverse estimation:$p(\boldsymbol{\theta}|x_{1:N}) \Leftrightarrow p(\boldsymbol{\theta}|x_{1:N},\mathbf{z}), with \mathbf{z} \sim N_5(\mathbf{z}|\mathbf{0},\mathbf{I})$. $\mathbf{z}$ can be set to follow a 5-dimensional unit normal distribution, to not disrupt the original correlation between $\boldsymbol{\theta}$ and $x_{1:N}$.

The posterior PDF estimation is then proposed to be realized through CINN with network parameters Φ [25], which tries to predict unit Gaussian distribution upon inputs of $\boldsymbol{\theta}$ and $x_{1:N}$. CINN is selected because of its unique Affine Coupling Block (ACB) structure, which facilitates the inverse calculation from network outputs to network inputs, as shown in Fig. 2.

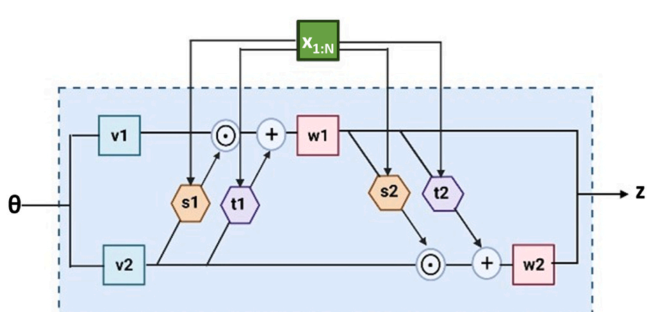

Fig. 2. Illustration of ACB structure.

The CINN segments the parameters into two sets, corresponding to two information flows, the connection between which is done through four separate sub-networks, s1, t1, s2, and t2. Each sub-network takes one subset of parameters and degradation data as inputs, and the four networks are subsequently stacked. Intuitively speaking, this configuration allows CINN to hierarchically decompose the degradation, in an order of determining parameters related to transient capacity changes first, as transient changes need to be evaluated in a global overview. The forward and backward operations of ACB structure are:

$$\begin{cases} w_1 = v_1 \odot \exp(s_1(v_2,x_{1:N}) + t_1(v_2,x_{1:N})) \\ w_2 = v_2 \odot \exp(s_2(w_1,x_{1:N}) + t_2(w_1,x_{1:N})) \end{cases} \tag{4}$$

$$\begin{cases} v_2 = (w_2 - t_2(w_1,x_{1:N})) \odot \exp(s_2(w_1,x_{1:N})) \\ v_1 = (w_1 - t_1(v_2,x_{1:N})) \odot \exp(s_1(v_2,x_{1:N})) \end{cases} \tag{5}$$

During the training phase, the training data mainly come from simulations that define appropriate ranges of parameters and generated degradation time series based on Eq. (3). In simulations, parameter ranges can be obtained from statistical analysis of practical data and should have good coverage of all possible degradation scenarios. Then the posterior estimation can be obtained as inverse calculation of network inputs $\boldsymbol{\theta}$ given samples generated from Gaussian distribution once the network is trained: $f_\Phi(\boldsymbol{\theta};x_{1:N}) = \mathbf{z} \Rightarrow \boldsymbol{\theta} = f_\Phi^{-1}(\mathbf{z};x_{1:N})$. The approach is based on an assumption that an appropriate network can compensate for the ambiguous mapping from $x_{1:N}$ to $\boldsymbol{\theta}$, and ideally achieves one-to-one mapping. The network training objective is proposed to minimize the Kullback-Leibler (KL) divergence [26] between the true and approximated posterior PDFs. Following the change of variable rule of probability [27], the network loss function is derived as:

$$\Phi = \arg\max_{\Phi} \int\int p(\theta,x_{1:N}) \log p_\Phi(\theta|x_{1:N}) d\theta dx$$
$$\Rightarrow \Phi = \arg\min_{\Phi} \int\int \begin{pmatrix} -\log p(z = f_\Phi(\theta;x_{1:N})) \\ -\log\left|\det\left(\dfrac{\partial f_\Phi(\theta;x_{1:N})}{\partial\theta}\right)\right| \end{pmatrix} d\theta dx \tag{6}$$

The first term in Eq. (6), evaluating the closeness of the predicted network outputs to the unit Gaussian distribution, can be quantified by $\|f_\Phi(\boldsymbol{\theta}; x_{1:N})\|_2^2$. The second term controls the convergence rate of the learning process of the nonlinear transformation from $\boldsymbol{\theta}$ to $\mathbf{z}$. Both terms in Eq. (6) can be easily calculated in CINN, and Eq. (6) can be realized through commonly used network training optimizers.

2.3. CINN for stochastic model parametric estimation

The training and inference phases of leveraging CINN for parametric estimation of the stochastic battery degradation model is shown in the flowchart Fig. 3.

As mentioned, the training of CINN can fully leverage simulation data, to cover a wide spectrum of degradation scenarios. Specifically, 64 batches of simulated data are generated from on Eq. (3), by sweeping through various values of model parameters, α, β, λ, and 5 distributions of R_k. The simulated capacity series are manually evaluated and rejected if their degradation trajectories do not look realistic. Training of the CINN maps the conditional probability of model parameters on simulated corresponding capacity series to unit normal distributions, with the dimension the latent space same as the dimension of model parameters (i.e., 4 or 5 depending on the distributions assumed for capacity regeneration magnitude R). Following the network training loss function specified in Eq. (6), iterative gradient descent can be implemented to adjust network parameters to minimize Eq. (6). The gradient calculation and backpropagation are implemented by the Adam optimizer, with a initial learning rate of 0.001 and an exponential decay rate of 0.95 to ensure convergence.

When applying the trained CINN for inference (i.e., estimating the stochastic model parameters), given a certain series of capacity degradation observations, 100 samples are first sampled from the unit normal distributions in the latent space. Leveraging the inverse calculation of CINN in Eq. (5), a set of model parameters' values can be calculated upon a single sample and capacity observation. Correspondingly, 100 sets of model parameter values will be generated, formulating an estimation of the posterior PDF. The estimated stochastic model can then be used to predict the capacity degradation at a future time. By setting a capacity threshold, the battery RUL can be predicted.

3. Simulation and experimental study

The proposed stochastic battery degradation model together with CINN-based model parametric estimation are evaluated on Li-ion battery simulations and run-to-failure tests provided in NASA's Battery Dataset.

3.1. NASA battery dataset

The NASA Li-ion Battery Dataset is publicly released in the NASA Ames prognostics data repository [28]. In the run-to-failure tests, individual batteries experienced extensive charge-discharge cycles, e.g., charging it to 4.2 V at 1.5 A and then discharging it over a 2 A load until the cell voltage hit 2.7 V. Depending on the battery, different charge-discharge curves and resting times between cycles were used. A battery was assumed to fail when the measured battery capacity dropped below 70% of its initial capacity. Samples of battery capacity degradation curves over charge-discharge cycles, as shown in Fig. 4, were normalized, considering different batteries had different initial capacities.

3.2. Battery degradation simulation

NASA Battery Dataset contains limited Li-ion battery run-to-failure tests, which are not enough to fully train CINN. Simulations are then generated upon Eq. (3) to complement experimental data. To determine appropriate ranges of model parameters, statistical regression analysis is performed on experimental data. The adopted parameter ranges for simulations are: $\alpha \sim U(0.70, 1.70)$, $\beta \sim U(3.15, 5.40)$, and $\lambda \sim U(0.05, 0.10)$. The λ range assumes that a capacity regeneration event occurs every 10–20 charge-discharge cycles. Five distributions are examined for the amplitudes of regeneration events: $s \sim U(0.0048, 0.0120)$ and $\vartheta \sim U(0.200, 0.400)$ for Gamma distribution, $\mu \sim U(0.70, 1.70)$ and $\sigma \sim U(0.70, 1.70)$ for Normal distribution, $m \sim U(0.018, 0.030)$ for Exponential distribution decays, $U(0.07, 0.08)$ for Uniform distribution, and κ

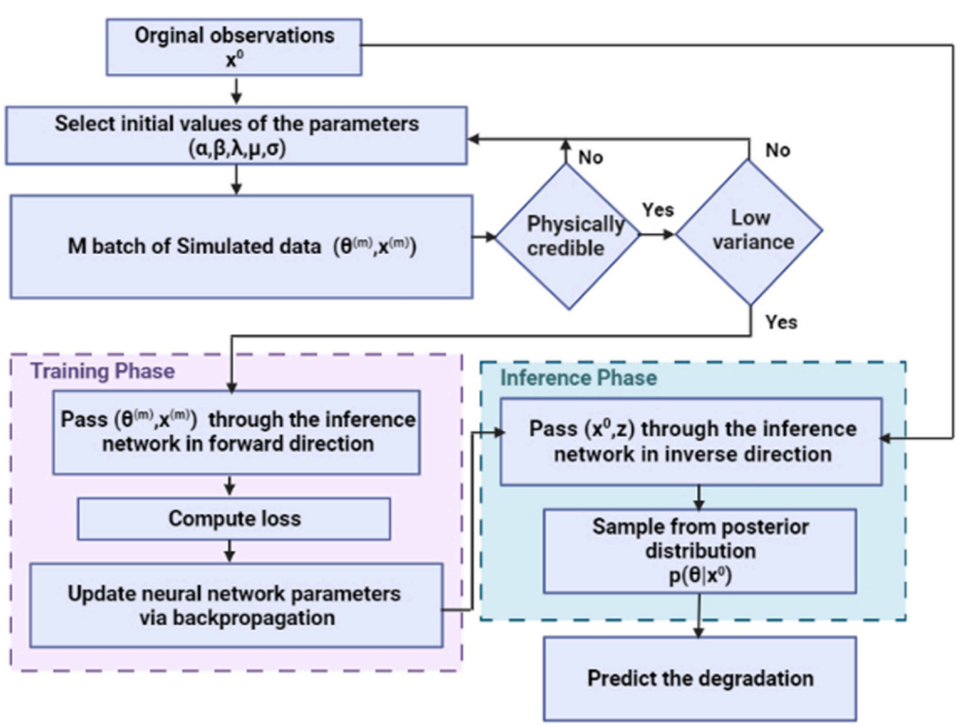

Fig. 3. Flowchart of CINN-based stochastic model parametric estimation, degradation tracking and prediction.

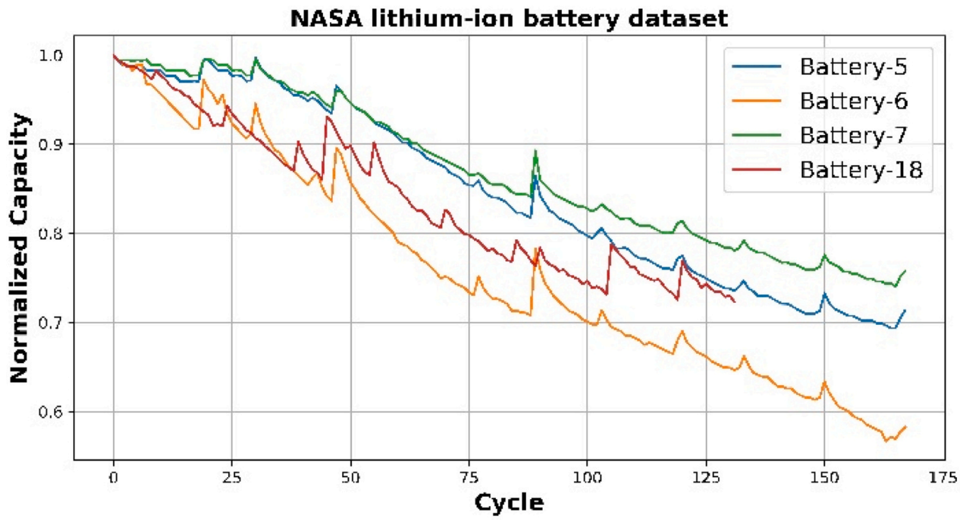

Fig. 4. Normalized capacity degradation of NASA lithium-ion battery datasets 5, 6, 7, and 18.

$\sim U(0.01, 0.03)$ for Chi-square distribution. 64 batches of simulation data, with 170 samples in each batch, are generated.

4. Results and discussions

After the CINN model training upon simulation data, the trained model was tested on NASA Battery Dataset. Trained model was provided by observed capacity observations throughout 75 or 100 cycles, and prognosis of capacity degradation were made after, as shown in Fig. 5 and Fig. 6. Overall, the rational polynomial model upon CINN-based parametric estimation tracks the gradual degradation well. Accurate prediction of capacity regeneration can be challenging, as it is difficult to accurately predict the regeneration moments, although an accurate estimation of regeneration event frequency may be obtained. Comparison of the 5 assumed amplitude distributions for regeneration events is summarized in Tables 1 and 2.

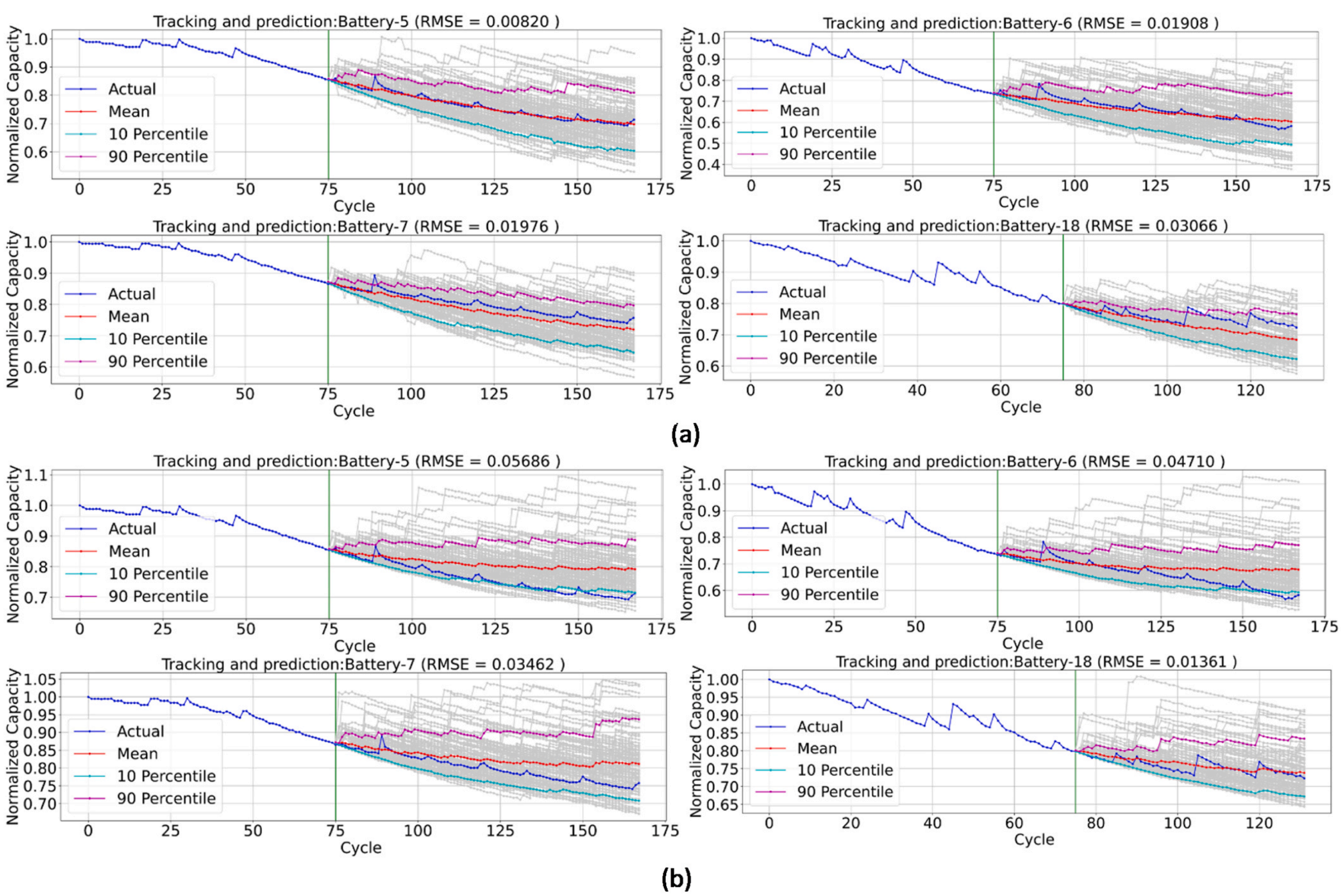

Fig. 5. CINN-based probabilistic prognosis made at 75th charge-discharge cycles, by assuming the amplitudes of the regeneration events following (a) normal distribution and (b) exponential distribution.

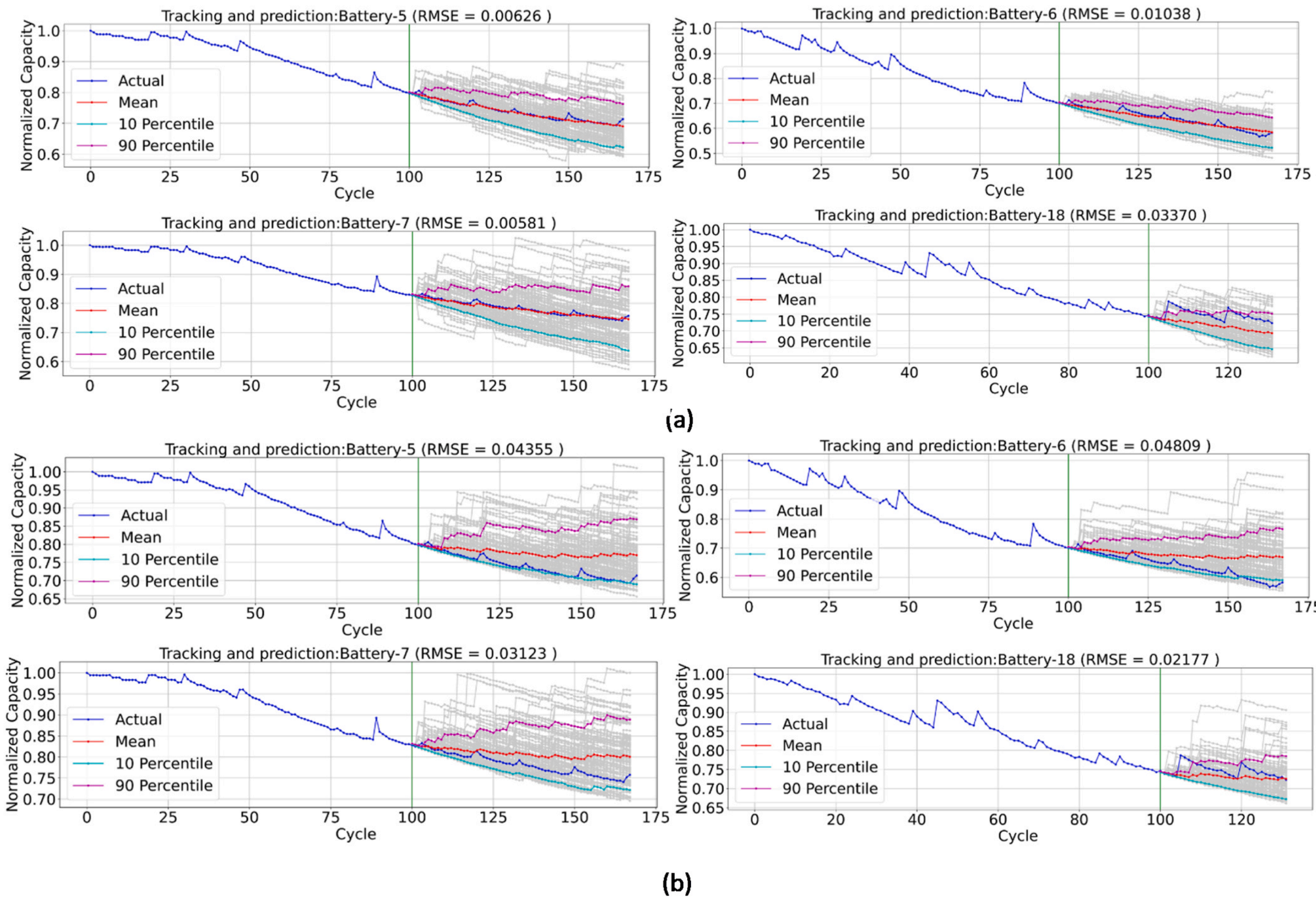

Fig. 6. CINN-based probabilistic prognosis made at 100th charge-discharge cycles, by assuming the amplitudes of the regeneration events following (a) normal distribution and (b) exponential distribution.

Table 1
Comparison of amplitude distributions of regeneration events, prognosis made at 75th cycle.

Battery #	Distribution				
	Gamma	Normal	Exponent	Uniform	Chi-square
5	0.0142	**0.0082**	0.0568	0.0087	0.0348
6	0.0329	**0.0190**	0.0471	0.0263	0.0477
7	0.0310	**0.0197**	0.0346	0.0301	0.0512
18	0.0336	0.0306	**0.0136**	0.0330	0.0495

Table 2
Comparison of amplitude distributions of regeneration events, prognosis made at 100th cycle.

Battery #	Distribution				
	Gamma	Normal	Exponent	Uniform	Chi-square
5	0.0082	**0.0062**	0.0435	0.0064	0.0200
6	0.0104	**0.0103**	0.0480	0.0128	0.0179
7	0.0183	**0.0058**	0.0312	0.0125	0.0334
18	0.0402	0.0337	**0.0217**	0.0392	0.0466

For prognosis based on the CINN parametric estimation method with the normal distribution, the prediction curves visually track better than the other distributions. Because CINN training is based on a collection of simulation data and follows the central limit theorem, it is straightforwardly assumed that the sample mean follows the normal distribution. The prognosis performance is furthermore quantitively evaluated in RMSE. The normal distribution for the amplitude of the regeneration events of the model exhibits the most accurate prediction for both prognoses after 75 and 100 cycles for Battery # 5, 6, and 7. Despite the narrow prediction intervals, the degradation curve of Battery # 18 is the only one that is not completely covered by the prediction interval. That is because that battery has two significant regeneration occurrences after 100 cycles, the intensity of which is out of the range of its historically shown capacity regeneration events that are used for CINN-based parametric estimation.

The best prognosis for Battery # 18 is generated by assuming an exponential distribution for capacity regeneration amplitude. This is because exponential distribution generates a wider range of estimation, suitable for tracking and predicting degradations with large fluctuations triggered irregular capacity regeneration events (e.g., two regeneration events after 100th cycle in Battery # 18). But it compromises prognosis precision, i.e., represented by the prediction confidence intervals. The uniform and gamma distributions demonstrate moderate accuracy while the Chi-square distribution shows the worst prognosis results.

A comparison between CINN-based parametric estimation and dominant Bayesian inference estimation techniques, PF and MCMC, is provided in Tables 3 and 4 for prognosis after 75 and 100 cycles respectively.

Overall, CINN-based parametric estimation for battery degradation tracking and prediction outperforms PF and MCMC methods. Particularly, significant prognosis accuracy (evaluated in RMSE) improvements are demonstrated in Battery # 6, and 7. RMSEs of predicted capacity made by MCMC and PF almost double the results generated by CINN with the normal distribution. As more data are used to estimate the model parameters, the prognosis after 100 cycles is better than the prognosis after 75 cycles, as is expected for all parametric estimation

Table 3
Comparison among CINN, PF and MCMC-based parametric estimation, prognosis made at 75th cycle.

Battery #	Parametric estimation method			
	CINN		PF	MCMC
	Normal	Exponential		
5	**0.0082**	0.0568	0.0181	0.0118
6	**0.0190**	0.0471	0.0412	0.0406
7	**0.0197**	0.0346	0.0460	0.0317
18	0.0306	**0.0136**	0.0262	0.0427

Table 4
Comparison among CINN, PF and MCMC-based parametric estimation, prognosis made at 100th cycle.

Battery #	Parametric estimation method			
	CINN		PF	MCMC
	Normal	Exponential		
5	**0.0062**	0.0435	0.0211	0.0134
6	**0.0103**	0.0480	0.0500	0.0138
7	**0.0058**	0.0312	0.0295	0.0116
18	0.0337	**0.0217**	0.0254	0.0423

methods.

For prognosis based on the CINN parametric estimation method with the normal distribution, the predicted capacity degradation trajectories visually look more similar to actual degradation trajectories than predictions by PF or MCMC methods (as demonstrated in [20]). In contrast to PF and MCMC that perform model training for individual batteries, CINN trains the model using a large amount of simulated data and only perform model parametric calculation for individual batteries. As a result, CINN exhibits improved modeling generalizability and estimation efficiency.

As discussed earlier, Battery # 18 is unique because of its abnormal capacity regeneration events during the prognosis phase, and CINN with exponential distribution achieved the best prognosis performance. If a normal distribution is assumed for the regeneration events, the average of estimation is the sample mean, and for Battery #18 the mean of the amplitudes of all historical regeneration events is lower than the mean of the amplitudes of the two regeneration events in the prediction stage. In this case, the prediction confidence interval, determined by both the global degradation variation and magnitudes of the regeneration events demonstrated in historical degradation behavior, is not able to constrain the regeneration events that behave differently from historical events in the prognosis.

To evaluate the repeatability and uncertainty associated with CINN-based parametric estimation, 50 independent runs are implemented for individual batteries. The results are shown in the bar graphs, Figs. 7 and 8, corresponding to CINN with normal and exponential distributions, respectively. Overall, CINN with normal distribution performs better with good repeatability and less uncertainty. Additionally, the results demonstrate that discrepancies between actual degradation and predictions are statistically insignificant, and ultimately prove the effectiveness of battery performance degradation tracking and prognosis based on the integration of developed advanced stochastic model with CINN-based parametric estimation.

The computational efficiency of CINN has also been compared to MCMC and PF, in terms of comparing the time required to perform a single run of tracking and parameter estimation. Tests were performed on a 2.1 GHz, 16-core Intel Xeon 6130 CPU with 192 GB of RAM, and NVIDIA Tesla V100 GPU with 24 GB of RAM. Averaged over 30 trials, CINN finished the 100 cycles input data-based parameter estimation in 0.2 s in average, while PF took 15 s and MCMC required 690 s, demonstrating the computational efficiency advantages of CINN-based parametric estimation for battery performance degradation tracking and prognosis.

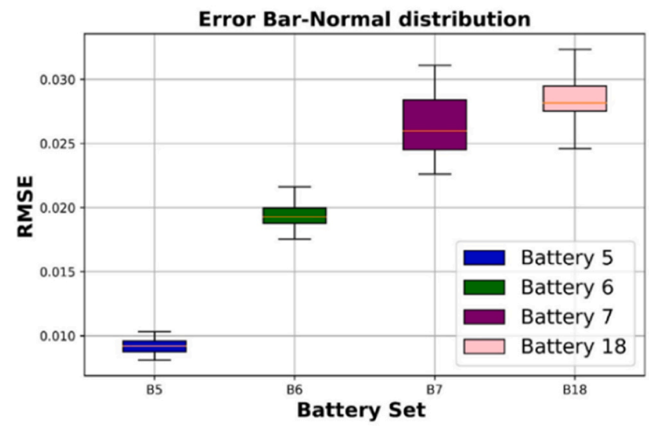

Fig. 7. Repeatability test and uncertainty evaluation for CINN-based parametric estimation with the amplitude of the regeneration events modeled as normal distribution.

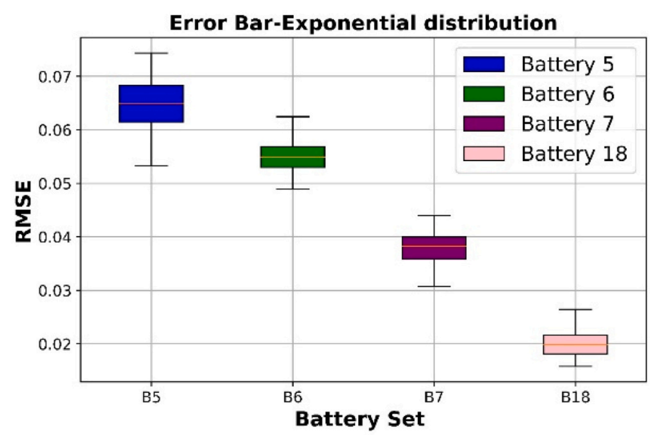

Fig. 8. Repeatability test and uncertainty evaluation for CINN-based parametric estimation with the amplitude of the regeneration events modeled as exponential distribution.

5. Conclusions

This paper presents a novel and efficient stochastic modeling and estimation method for battery performance degradation tracking and prediction, by integrating the advanced stochastic model developed from our previous work with CINN-based parametric estimation. Compared to conventional Bayesian inference estimation techniques such as PF and MCMC, CINN can be trained on simulation data that can cover a broad spectrum of degradation scenarios, thus demonstrating better modeling generalizability. Also, CINN only performs straightforward calculation without retraining during the inference phase for individual batteries, hence improving the prognosis efficiency. Experimental studies on NASA Battery Dataset show significant prognosis improvements by CINN than conventional PF and MCMC-based parametric estimation methods. In further studies, Lévy process-based stochastic modeling will be examined with the CINN parametric estimation in place of the CPP model to better capture and describe regeneration events.

CRediT authorship contribution statement

Peng Wang: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Lakmali Nadeesha:** Data curation, Formal analysis, Methodology, Software, Validation, Writing – original draft.

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.

Acknowledgements

This work is supported by the National Science Foundation under Grant No. 2015889.

References

[1] Yu L, Xiao H, Li X, Zhu R, Huai R. Model parameter identification for lithium batteries using the coevolutionary particle swarm optimization method. IEEE Trans Ind Electron 2017;64:5690–700. https://doi.org/10.1109/TIE.2017.2677319.
[2] Pelletier S, Jabali O, Laporte G, Veneroni M. Battery degradation and behaviour for electric vehicles: review and numerical analyses of several models. Transp Res Part B 2017:158–87.
[3] Witczak M, Majdzik P, Stetter R, Lipiec B. A fault-tolerant control strategy for multiple automated guided vehicles. J Manuf Syst 2020;55:56–68.
[4] Lu S, Xu C, Zhong RY, Wang L. A RFID-enabled positioning system in automated guided vehicle for smart factories. J Manuf Syst 2017;44:179–90.
[5] De Ryck M, Versteyhe M, Shariatmadar K. Resource management in decentralized industrial automated guided vehicle systems. J Manuf Syst 2020;54:204–14.
[6] Jimenez JJM, Schwartz S, Vingerhoeds R, Grabot B, Salaün M. Towards multimodel approaches to predictive maintenance: a systematic literature survey on diagnostics and prognostics. J Manuf Syst 2020;56:539–57.
[7] Qu J, Liu F, Ma Y, Fan J. A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery. IEEE Access 2019;7:87178–91. https://doi.org/10.1109/ACCESS.2019.2925468.
[8] Wang F, Sun J, Liu X, Liu C. Aircraft auxiliary power unit performance assessment and remaining useful life evaluation for predictive maintenance. Proc Inst Mech Eng Part A J Power Energy 2020;234(6):804–16.
[9] Barré A, Deguilhem B, Grolleau S, Gérard M, Suard F, Riu D. A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. J Power Sources 2013;241:680–9.
[10] Vykhodtsev A. Development of physics-based models of lithium-ion battery energy storage for power system techno-economic studies. Development 2023;2023: 09–21.
[11] Downey A, Lui YH, Hu C, Laflamme S, Hu S. Physics-based prognostics of lithium-ion battery using non-linear least squares with dynamic bounds. Reliab Eng Syst Saf 2019;182:1–12.
[12] Jafari M, Khan K, Gauchia L. Deterministic models of Li-ion battery aging: it is a matter of scale. J Energy Storage 2018;20:67–77.
[13] Tao L, Ma J, Cheng Y, Noktehdan A, Chong J, Lu C. A review of stochastic battery models and health management. Renew Sustain Energy Rev 2017;80:716–32.
[14] Wang Z, Wang S, Yu C, Qiao J. Improved long short-term memory: statistical regression model for high precision soc estimation of lithium-ion batteries adaptive to complex current variation conditions. J Electrochem Soc 2023;170(5):050521.
[15] Zhao G, Zhang G, Liu Y, Zhang B, Hu C. Lithium-ion battery remaining useful life prediction with deep belief network and relevance vector machine. 2017 IEEE Int Conf Progn Health Manag (ICPHM) 2017:7–13.
[16] Qu J, Liu F, Ma Y, Fan J. A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery. IEEE Access 2019;7:87178–91.
[17] Ren L, Zhao L, Hong S, Zhao S, Wang H, Zhang L. Remaining useful life prediction for lithium-ion battery: a deep learning approach. IEEE Access 2018;6:50587–98.
[18] Xu L., Deng Z., Xie Y., Lin X., Hu X. A novel hybrid physics-based and data-driven approach for degradation trajectory prediction in Li-ion batteries. IEEE Trans Transp Electrification 2022.
[19] Peng D, Wen C, Lv M. Design of a high-order Kalman Filter for State and Measurement of A Class of Nonlinear Systems Based on Kronecker product augmented dimension. Sensors 2023;23(6):2894.
[20] Russell MB, King EM, Parrish CA, Wang P. Stochastic modeling for tracking and prediction of gradual and transient battery performance degradation. J Manuf Syst 2021;59(7):663–74.
[21] Chen Y, He Y, Li Z, Chen L, Zhang C. Remaining useful life prediction and state of health diagnosis of lithium-ion battery based on second-order central difference particle filter. IEEE Access 2020;8:37305–13.
[22] Wang P, Gao RX. Prognostic modeling of performance degradation in energy storage by lithium-ion batteries. Proc Manuf 2019;34:911–20.
[23] Liu JS, Chen R. Sequential Monte Carlo methods for dynamic systems. J Am Stat Assoc 1998;93:1032–44.
[24] Astfalck L, Hodkiewicz M. Hamiltonian Monte Carlo sampling for Bayesian hierarchical regression in prognostics. PHM Soc Asia Pac Conf 2017;1:1.
[25] Dinh L., Sohl-Dickstein J., Bengio S. Density Estimation Using real NVP, 5th Int Conf Learn Represent ICLR 2017 - Conf Track Proc; 2017.
[26] Painsky A, Wornell GW. Bregman divergence bounds and universality properties of the logarithmic loss. IEEE Trans Inf Theory 2020;66:1658–73.
[27] Dekking FM, Kraaikamp C, Lopuhaä HP, Meester LE. A modern introduction to probability and statistics: understanding why and how. Springer Science & Business Media,; 2005.
[28] Saha B, Goebel K. Modeling Li-ion battery capacity depletion in a particle filtering framework. Annu Conf PHM Soc 2009;1:1.