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Early RUL Prediction for Fast-charging Power Battery Based on Hybrid Modeling

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Abstract. *Nowadays, countries worldwide are actively promoting the development of new energy electric vehicles, and the performance and lifetime of power batteries, as the core components of new energy EVs, play a crucial role in the reliability and sustainability of the vehicles. Therefore, accurate prediction of EV batteries' Remaining Useful Life (RUL) is necessary. However, the gradual degradation of battery capacity in the early stages often makes early battery RUL prediction more challenging. This work proposes a novel hybrid method to predict battery RUL with fewer battery cycles, introducing the Efficient Channel Attention mechanism. The proposed method could better capture the subtle changes in the early stage of the battery, thereby providing improved capability to capture contextual information and enhancing the accuracy of the RUL prediction. Additionally, the Adaptive Dropout is introduced into the model to capture the essential attributes of battery lifespan from various complex factors battery for the RUL prediction. Extensive experiments are conducted on a real dataset, and the results demonstrate that the proposed method effectively improves the prediction performance with fewer cycles and achieves an earlier prediction.*
Keywords: electric vehicle, battery remaining useful life, Efficient Channel Attention, adaptive dropout, early prediction

1. **Introduction.** Global environmental challenges are growing increasingly severely. Nations are acknowledging the adverse impact of conventional fuel vehicles on the environment. Governments, automakers, and technology firms are intensifying their investments in and promotions of new-energy electric vehicle technologies to curb carbon emissions and enhance air quality [1, 2]. According to pertinent data, most electric vehicle (EV) fire incidents stem from battery pack thermal runaway, accounting for 38.1% of all safety accidents. Thus, accurately projecting EV batteries'RUL [3] beforehand becomes imperative to avert thermal runaway accidents involving electric vehicles. Currently, most RUL predictions are based on cycle data exhibiting initial capacity degradation exceeding 5% [4–7].

However, the development and production of batteries with prolonged cycle life usually span months or even years, potentially causing feedback performance delays. Kristen et al., for instance, suggested that utilizing early cycle data for battery RUL prediction could expedite the battery development cycle. Manufacturers could promptly validate fresh manufacturing processes and evaluate batteries for their anticipated lifespans [8]. Nonetheless, given the nonlinear nature of battery degradation influenced by cycle counts and usage conditions, precise RUL prediction poses a daunting task. This challenge becomes even more pronounced when predictions hinge solely on early cycle data. Early-stage battery degradation typically occurs sluggishly, followed by accelerated deterioration at specific intervals or after a particular number of cycles [9]. However, directly feeding substantial raw data into deep networks proves impractical due to inherent noise and redundant information, which could lead to sluggish model convergence and diminished prediction accuracy. The challenge is particularly pronounced in capturing subtle shifts during the early battery stages when capacity degradation isn't readily apparent. **Figure 1** showcases the capacity degradation process of a power battery across a cycle, in which the insignificance of capacity degradation in the battery's early stages is evident. In this work, we proposed a novel method to predict RUL with fewer cycles and to forecast battery life early.

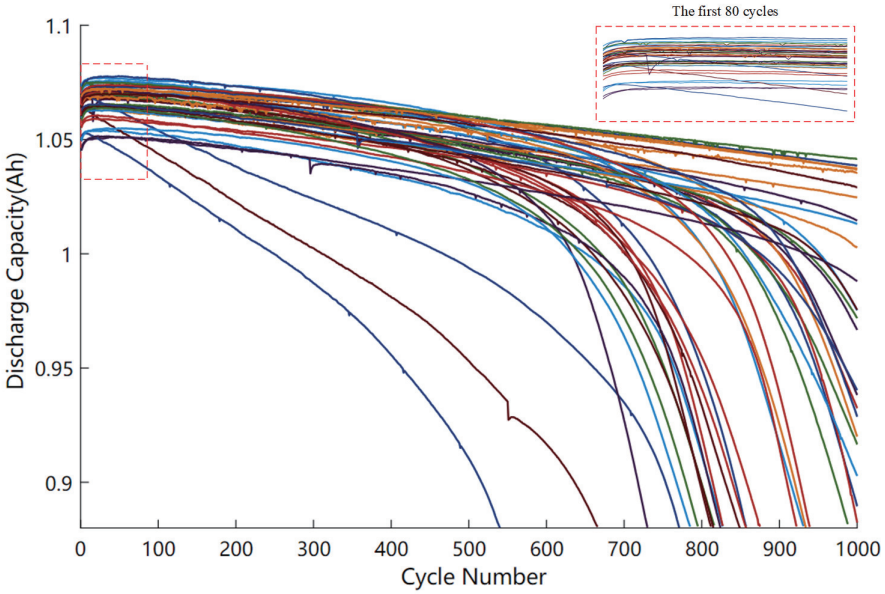

FIGURE 1. Battery capacity degradation curves.

Model-based and data-driven approaches are two kinds of approaches to predicting the RUL of batteries. The model-based approaches aim to develop a mathematical model

to depict the degradation of battery dynamically, providing a precise portrayal of the battery degradation process. For instance, Zheng et al. [10] proposed estimating the RUL of lithium-ion batteries using a physical degradation model and a traceless Kalman filter . Similarly, Liu et al. [11, 12] suggested utilizing kinetic and physical models based on the electrochemistry of lithium-ion batteries to simulate their current and voltage characteristics.

Developing accurate battery RUL prediction models generally necessitates profound domain knowledge, particularly a comprehensive of battery degradation mechanisms [13,14]. Model-based approaches, however, often lack the flexibility to capture uncertainties stemming from external environment changes, variations in operational conditions, and material and manufacturing differences. In contrast, data-driven approaches involve analyzing historical battery cycling data to build models inferring RUL through machine learning techniques. For example, Peng et al. [15] developed a unified feature selection method called Local Structure Preservation based on Feature Selection (LSPFS) to improve the robustness and accuracy of forecasting under unsupervised and supervised learning conditions on a lithium-ion battery dataset. In LSPFS, the local structure of the original data is constructed based on the similarity between data points, while representative features are selected based on their ability to preserve the local structure. In addition, by designing different local structures through the data's local and actual degradation information, the approach could unify supervised and unsupervised feature selection and then learn from them jointly under a common framework.

Wu et al. [16] employed a feedforward neural network to establish a relationship between battery RUL and variations in constant current charging voltage profiles under distinct cycles. Zhang et al. [6] attempted training Long Short-Term Memory networks to grasp the long-term dependency between degraded capacities. Early battery RUL prediction remains elusive. Despite their higher flexibility and applicability, data-driven methods still have undisclosed mechanisms and information transfer rules. Additionally, a critical challenge arises from the potential inaccuracies or entirely wrong predictions due to insufficient or biased battery data. In recent years, integrating model-based and data-driven methods has emerged as a pivotal research focus for enhancing accuracy in battery RUL prediction. This hybrid approach optimally leverages the respective strengths of both methods. For instance, Xu et al. [17] proposed a hybrid deep network model for early battery RUL prediction. It combines manual features with domain knowledge and latent features learned from deep networks to enhance early RUL prediction performance, Nonetheless, the model lacks substantial attention to subtle data changes and doesn't dynamically adapt neuron retention or discard rates based on actual battery conditions, resulting in limited generalization and accuracy, especially with a constrained number of cycles.

To address the challenges, a comprehensive approach is proposed in this work, which integrates expert knowledge features from the battery domain and potential attributes for neural network learning. Leveraging the Convolutional Neural Networks (CNN) encoder, local statistical features are extracted and channeled into an Efficient Channel Attention (ECA), which captures subtle battery changes, enhancing feature aggregation and resulting in accurate RUL prediction with fewer cycles. Simultaneously, local statistical features grounded in domain knowledge are harnessed and introduced into a fully connected network comprising interconnected layers. Further, the proposed model integrates two adaptive dropout layers following the CNN encoder and the fully connected network. These layers dynamically regulate the number of neuron outputs based on data features. Additionally, fully connected layers are employed to map the interconnected features to

the ultimate target. The main contributions of this work could be summarized as follows:

1. A hybrid prediction model is proposed to integrate the features of domain knowledge and statistics features, and the ECA mechanism is introduced to capture slight changes from early cycles and enable earlier RUL forecasts.
2. An adaptive dropout technique is introduced to adaptively process diverse data in various scenarios during the training and bolster prediction accuracy.
3. Extensive experiments were conducted on a real-world dataset, showing that the proposed model significantly improves the prediction capability. Compared with the existing related models, which require more than 100 cycles, the proposed model improves the prediction accuracy with fewer cycles and then achieves an early RUL prediction.

The rest of the paper is organized as follows. Section II reviews some related works on battery RUL prediction. Section III describes the details of the proposed method, including the ECA module to capture the early battery minutiae changes and adaptive dropout retention features and the structure of the hybrid model for early RUL prediction of fast-charging power batteries. Section IV describes the dataset, experimental environment, evaluation metrics, and experimental details. Section V discusses and analyzes the experimental results. Section VI summarizes the work and suggests directions for future work.

2. **Realted work.** For manufacturers of new energy electric vehicles, accurate prediction of the RUL of batteries holds the potential to enhance the design of longer-lasting and more efficient products, resulting in improved user experience and product performance. In recent years, research teams have made significant strides in predicting battery RUL. To illustrate, Hu et al. [18]conducted a comprehensive review of battery RUL prediction techniques, focusing on recent advancements in model-based, data-driven, and hybrid model algorithms. They diligently analyzed and compared these methods' particulars, advantages, and limitations. Similarly, Xing et al. developed an integrated model to characterize battery capacity degradation. This model leverages the analysis of experimental data and incorporates empirical exponential and polynomial regression models to track battery degradation trends throughout its life cycle.

Additionally, they employed a particle filter algorithm for online adjustment of model parameters [19]. Moreover, Pang et al. [20] simultaneously employed a Kalman filter and an expectation-maximization algorithm to estimate battery capacity degradation. Zhang et al. [6] on the other hand, proposed utilizing a long and short term memory neural network for battery RUL prediction. This network captures potential long-term dependencies among degraded battery capacities and is coupled with Monte Carlo simulation to generate battery RUL predictions. Along similar lines, Bloom et al. [21], and Broussely et al. [22] employed semi-empirical models to predict performance and capacity losses during the early stages of the battery. In another approach, Liu et al. presented an optimized Nonlinear degenerate-auto regressive time series model for estimating Li-ion battery RUL, which facilitates multi-stage prediction of battery capacity degradation state.

Furthermore, to enhance the representation capability of classical particle filtering (Sampling Importance Resampling) for uncertainty, a Li-ion battery RUL fusion estimation framework [4] is devised, utilizing the regularized particle filter. This methodology is also applied to the battery RUL fusion estimation framework [23]. Ardeshiri and Ma [24] proposed the approach of a gated recurrent unit recurrent neural network, which extracts ample statistical features from voltage, current, and temperature measurements in each cycle. Additionally, the authors employed linear correlation and random forests to reduce

the feature dimension further. Despite demonstrating the effectiveness of machine learning techniques in predicting battery RUL, these methodologies heavily rely on data from the battery degradation curve, specifically needing to ascertain the point at which battery degradation initiates. Typically, model training involves utilizing a cyclic data volume spanning from 40% to 70% of the complete battery life cycle [18, 25–28] . Nevertheless, this approach that hinges on the degradation curve may harbor several limitations. Initially, it necessitates amassing and employing a significant amount of cyclic data, which can be challenging in scenarios where the battery's lifespan is extensive or data collection costs are high. Moreover, due to the requirement of identifying zones where battery degradation commences for training, subtle changes occurring in the battery's early stages might elude detection, thereby making it hard to predict the early RUL.

In recent years, hybrid methods combining model-based and data-driven approaches have amalgamated the relative advantages, emerging as a prominent research focus in battery RUL prediction. Broadly speaking, hybrid methods can be categorized into three types based on diverse processing techniques:

(1) Enhancing the performance of filtering methods. For instance, He et al. amalgamated data from various sources through information fusion grounded in the Dempster-Shafer theory. Subsequently, they employed Bayesian Monte Carlo to update the model parameters and formulated an RUL prediction model for lithium-ion batteries using the accessible battery capacity monitoring data [25]. Zhang et al. [29] introduced an Improved Unscented Particle Filter approach for RUL prediction of Li-ion batteries, rooted in the Markov chain Monte Carlo principle. This method employs Markov chain Monte Carlo to address the RUL prediction of Li-ion batteries, including the resolution of the sample depletion issue in the Unscented particle filter algorithm.

(2) Generating future observations. For instance, Chang et al. employed the Unscented Kalman Filter algorithm to produce the initial error sequence. They then analyzed the outcomes of the Complementary Ensemble Empirical Mode Decomposition algorithm to form a new error sequence, which was subsequently employed to predict errors through the relevance vector machine regression model. This new error sequence is created by examining the decomposition outcomes of the original error sequence acquired through the Complementary Ensemble Empirical Mode Decomposition algorithm. The new error sequence is then employed to forecast prediction errors using the relevance vector machine regression model, consequently rectifying the prediction outcomes of traceless Kalman filtering [30]. Similarly, Song et al. [31] proposed a hybrid approach that integrates an iterative nonlinear degradation-auto regressive model and a particle filter algorithm. This approach enhances long-term prediction performance by incorporating nonlinear degradation factors and iterative parameter updating, utilizing the capacity prediction outcomes as the measurement function within the particle filter algorithm.

(3) Data enhancement. For instance, Yu et al. [32] proposed a method that combines multiscale logistic regression and Gaussian process regression. Empirical mode decomposition is utilized to separate the global degradation, local regeneration, and various fluctuations of the battery capacity time series. Residuals representing the overall degradation trend were modeled using a variable moving window LR model. A ground-penetrating radar with lag vectors is suggested for recursive estimation of local regeneration and fluctuations. As previously mentioned, researchers in battery RUL prediction have primarily employed data from NASA [33], CALCE [34], or private battery cycling data. These datasets are predominantly acquired under constant current constant voltage cycling conditions, with the batteries tested at a constant temperature.

However, operating conditions exhibit high variability in most battery-powered applications, and batteries experience numerous dynamic degradation mode shifts. Furthermore, owing to rapid advancements in battery technology, the performance and lifespan of batteries have considerably improved. Consequently, investigating the aging behavior of batteries under dynamic and demanding operating conditions has gained significant importance. Moreover, Xu et al. [17] introduced a hybrid model that integrates domain knowledge features and potential features acquired from neural networks for early RUL prediction. Nevertheless, the model struggles to detect subtle changes in the early battery stage, curtailing its early prediction capabilities. Additionally, it necessitates manual tuning of the failure rate, introducing certain uncertainties.

3. Methodology.

3.1. **Overview.** For the early battery RUL prediction problem, this work proposed a hybrid model to combinate feature patterns and domain knowledge, as shown in **Figure 2**, including a CNN encoder to deal with the local statistical features and a fully connected network to deal with the domain knowledge features. In this work, we combined

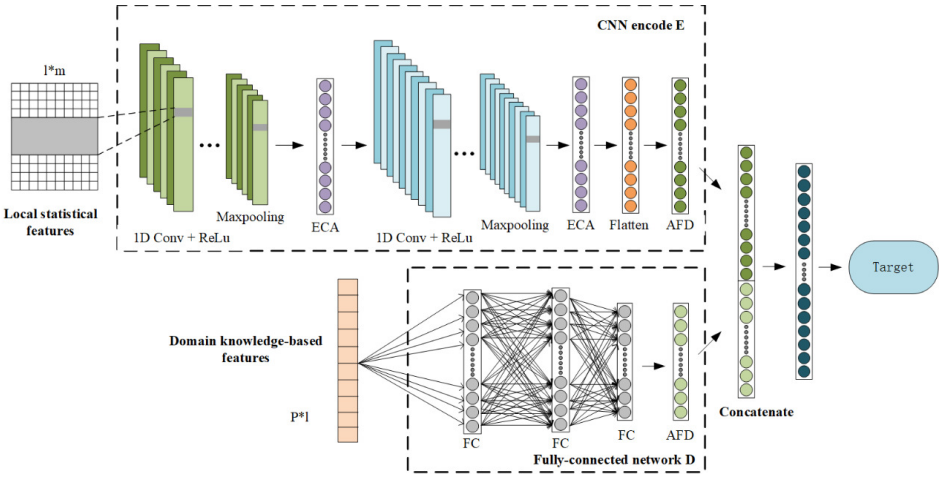

FIGURE 2. Hybrid model structure.

an expert-based domain method proposed by Qing et al. [17] that extracts expert-based domain knowledge features with latent features learned by neural networks. We utilize the data set collected by Kristen et al. [8] along with 20 statistical features: Var_dQ_80_10, min_dQ_80_10, mean_dQ_80_10, slope_Qd_cycle_71_80, Qd_2, Qd_80, min_ir_cycle_2_80, ir_diff_cycle_80_2. By incorporating the ECA mechanism to focus on subtle changes in important features, we achieve enhanced battery RUL prediction efficiency using fewer cycles and improved prediction accuracy.

Additionally, this work introduces an adaptive dropout mechanism to dynamically adjust the failure probability of neurons based on the data's characteristics. Meanwhile, the proposed method addresses the issue in Qing et al.'s work [17] about the dropout mechanism with a fixed probability for neuron failure. Consequently, the approach better retains features and enhances model training efficiency and generalization ability.

3.2. **Enhanced Channel Attention.** Considering the nature of early battery changes, this work aims to capture these initial battery alterations and contextual information accurately. To achieve this, a lightweight ECA mechanism is integrated as depicted in **Figure 3**. The mechanism is employed to generate the channel attention, which dynamically adjusts the kernel size to align with the channel size of the nonlinear mapping using

rapid one-dimensional convolution. The improvement contributes to enhanced computational efficiency and the generalization capability of CNN, and then the model facilitates precise battery RUL prediction with a reduced number of cycles. The module employs a

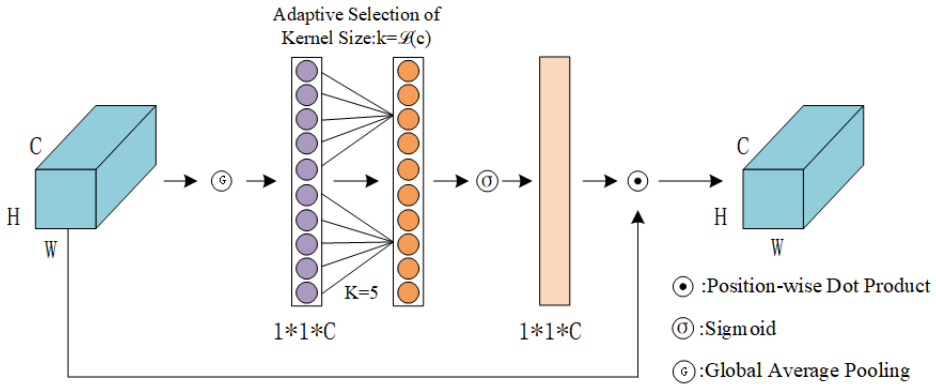

FIGURE 3. Efficient channel attention.

global average pooling operation to process the input data for extracting global features. Then, a fast one-dimensional convolution operation with dimensions $K * 1$ and activation with the Sigmoid function are integrated to obtain the channel weights.

$$K = \varphi(C). \tag{1}$$

In the module, the K is adaptively determined based on the channel dimension C, and the channel weights W are calculated as shown in Equation (2).

$$W = \sigma(C1D_K(y)). \tag{2}$$

where $C1D$ indicates $1D$ convolution and the method in Equation (2) is called by the ECA module, which only involves K parameters. The weights are employed to multiply with the corresponding elements of the original input features to produce the final output features.

$$Output = C * W. \tag{3}$$

3.3. **Adaptive Dropout.** The dropout algorithm, known as a method to sparse networks, improves model accuracy by training multiple subnetworks and shows a high training time complexity. However, the model suffers from problems such as corrupted learning features and the difficulty in manual parameterization. For this reason, this work proposed an adaptive dropout algorithm as shown in **Figure 4**.

The algorithm adaptively estimates the probability values in the traditional dropout algorithm based on the distribution and characteristics of the data to better retain the features and improve the training efficiency and generalization ability of the model. where the outputs of the attentional mechanism and the domain feature fully connected layer are used as the input x of the adaptive dropout, respectively, and the activation value a is obtained by applying the activation function ReLU to the input x:

$$a = ReLU(x). \tag{4}$$

$$P = softmax(a). \tag{5}$$

where the importance score is mapped to between 0 and 1 using the softmax function to obtain the retention probability P for each neuron.

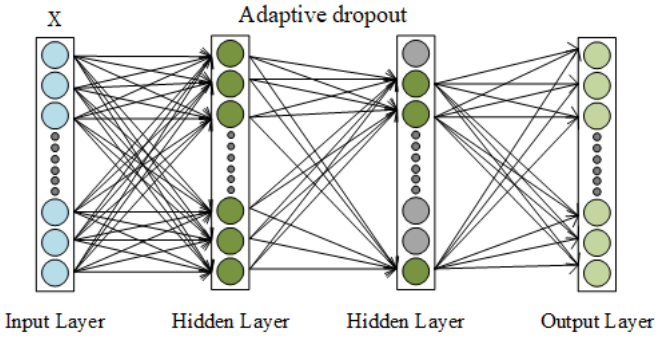

FIGURE 4. Adaptive dropout network diagram.

$$a_{masked} = a \odot p. \tag{6}$$

where $\odot$ denotes the multiplication of each element. In the step, the activation value a is multiplied by the retention probability p to obtain the final activation value a_{masked},

3.4. **Hybrid Model.** To extract as much useful information as possible from the measurement data, we propose a hybrid model that combines domain knowledge-based features and local statistical features as inputs, as shown in **Figure 2**. The local statistical features are first extracted using a CNN encoder E, where the one-dimensional CNN architecture of the encoder is used to capture temporal dependencies between time series data, thus achieving higher computational efficiency than recurrent neural networks and more stable backpropagation properties.

The maximum pooling layer is also used to retain essential features and improve model accuracy. Next, the critical features are fed into the ECA mechanism [35]. The ECA mechanism layer is employed to capture small changes in the battery and improve the feature aggregation, enabling accurate RUL prediction results to be obtained with fewer cycles. Simultaneously, the domain knowledge is tapped into to acquire local statistical features with dimensions $n * l * m$, where n represents the number of samples, l signifies the total number of statistical features, and m indicates the number of loops. The selected domain features rooted in expert knowledge are input into a fully connected network D, comprising a sequence of fully connected layers with dimensions $n * p$, where n represents the number of samples and p denotes the number of features specific to the chosen domain.

Lastly, the high-dimensional features are mapped, flattened, and interconnected. To counteract overfitting, two adaptive dropout layers [36], are incorporated after the CNN encoder E and the fully connected network D, prior to the cascade operation. This results in an automatic adjustment of the number of neuron outputs based on data features. Subsequently, the fully connected layer is utilized to map the interconnected features to the final target. The optimization of the hybrid model involves minimizing the loss concerning the true label y.

4. Experiments and Results.

4.1. **Datasets and experimental environmental.** To evaluate the proposed method, the work employed a dataset provided by the Massachusetts Institute of Technology, Stanford University, and the Toyota Research Institute [8]. The dataset consists of 124 lithium-iron-phosphate/graphene batteries that record the cycle life of the batteries under different conditions by intentionally changing the charging conditions. The batteries were used for approximately 150 to 2300 cycles (mean cycle life of 806, standard deviation of

377). Voltage, current, battery case temperature, and internal resistance were measured during the cycles.

There are three sets of battery data in this dataset: a training set, an initial test set, and an aging test set. The training set and initial test set are battery pack data sets collected over the same period, and the aging data set is a battery pack data set collected after approximately one year. **Table 1** shows the experimental hardware and software configuration. More detailed information about this battery dataset can be found at https://data.matr.io/1/.

The versions of Python and PyTorch used in this paper's experiment are 3.7.12 and 1.13.0. The experiments were done on a Linux server equipped with an NVIDIA GeForce RTX 3090 graphics card with 24GB of video memory, 128GB of RAM, and an Intel Core i7-11700 processor with 8 cores and 16 threads.

4.2. **Assessment of indicators.** In this work, we use Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to evaluate the model's performance. RMSE is defined in Equation (7), and MAPE in Equation (8).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{y}_i - y_i)^2}. \tag{7}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\bar{y}_i - y_i}{y_i}\right|. \tag{8}$$

4.3. **Experimental result.** The results of the proposed method are shown in **Figure 5**, from which it can be seen that our algorithm used in this paper does not show a significant difference between RMSE and MAPE at measurements of 80, 90, and 100 cycles. The method in this work is effective in delaying the deterioration of the predicted RUL effect. Therefore, choosing a smaller number of cycles for the experiment can predict RUL earlier and improve the safety of the battery. In order to assess the effectiveness of the proposed hybrid model, we compared it with the various methods listed in **Table 1** and **Table 2**.

Table 1. RMSE and MAPE values for different methods on the initial test set

Methods	Cycle Index	Initial test set	
		RMSE	MAPE
Elastic-V [8]	100	138.39	13.19
Elastic-D [8]	100	170.35	10.99
Elastic-F [8]	100	117.64	9.25
SVR-V [37]	100	170.72	14.72
NN-F [38]	100	116.54	9.13
LSTM [6]	100	166.87	18.05
CNN-LSTM [39]	100	176.63	14.85
GRU-RNN [24]	100	127.65	9.94
PSR-SVR [40]	100	191.83	20.3
Qing et al. [17]	100	114.05(SD:2.47)	8.54(SD:0.07)
Ours	**80**(↑ 20%)	**116.28(SD:1.16)**	**8.56(SD:0.05)**

In this work, we use RMSE and MAPE to evaluate the 11 models in **Table 1** and **Table 2** on both the initial and aging test sets. The models Elastic-V, Elastic-D, and Elastic-F represent the "variance", "discharge", and "full" feature set trained elastic networks, respectively. Elastic networks are trained on the "variance", "discharge", and "complete"

TABLE 2. RMSE and MAPE values for different methods on the Aging test set

Methods	Cycle Index	Aging test set	
		RMSE	MAPE
Elastic-V [8]	100	196.01	11.41
Elastic-D [8]	100	179.64	14.2
Elastic-F [8]	100	225.72	12.85
SVR-V [37]	100	226.79	12.11
NN-F [38]	100	225.83	12.87
LSTM [6]	100	380.85	22.66
CNN-LSTM [39]	100	375.47	25.25
GRU-RNN [24]	100	356.31	34.17
PSR-SVR [40]	100	404.57	32.93
Qing et al. [17]	100	177.88(SD:1.77)	11.31(SD:0.23)
Ours	**80**(↑ 20%)	**180.56(SD:1.54)**	**11.29(SD:0.18)**

feature sets, respectively [8]. Additionally, we evaluate other machine learning-based methods such as SVR [37], NN [38], LSTM [6], CNN-LSTM [39], GRU-RNN [24], PSR-SVR [40], and Qing et al. [17], which are also tested using datasets provided by the Massachusetts Institute of Technology (MIT), Stanford University, and the Toyota Research Institute (TRI) [8]. The results are shown in **Figure 6** and **Figure 7**. Based on the experimental results, the results of predicting the battery RUL using only the first 80 cycles are better than the results of predicting the battery RUL using the first 100 cycles for the following models: Elastic-V, Elastic-D, Elastic-F, SVR, NN, LSTM, CNN-LSTM, GRU-RNN and PSR-SVR. Using the first 80 cycles to predict the battery RUL, the results in this paper are close to Qing's results using the first 100 cycles to predict the battery RUL, and even the standard deviation values are smaller than Qing's [17] method.

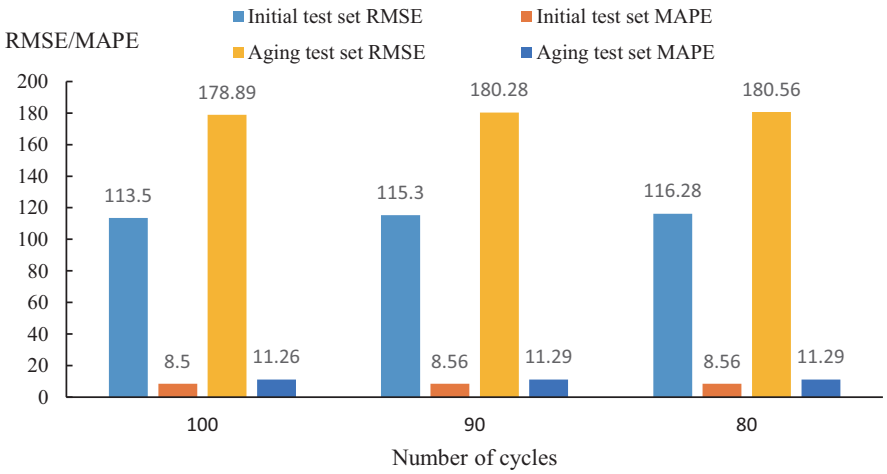

FIGURE 5. The effort of different cycle times on RUL prediction.

5. **Discussion.** Experimental results show that Different feature sets usually result in different performances on the two test sets. For example, the results in **Table 2** show that Elastic-V performs better in terms of RMSE and MAPE on the Aging test set compared to Elastic-F. As the results in **Table 1**, Elastic-D performs worse on the Initial test set. SVR-V uses the same feature set as Elastic-V, but performs worse. These results show

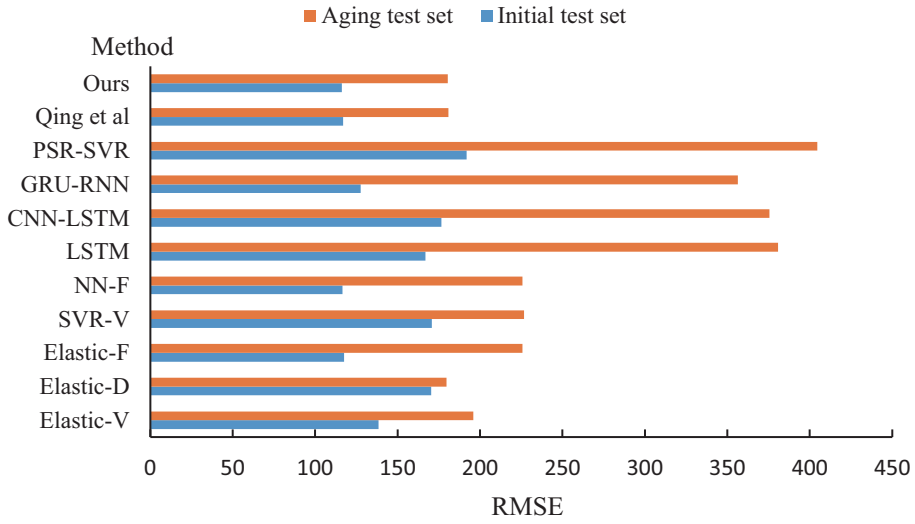

FIGURE 6. Different algorithm RMSE varies.

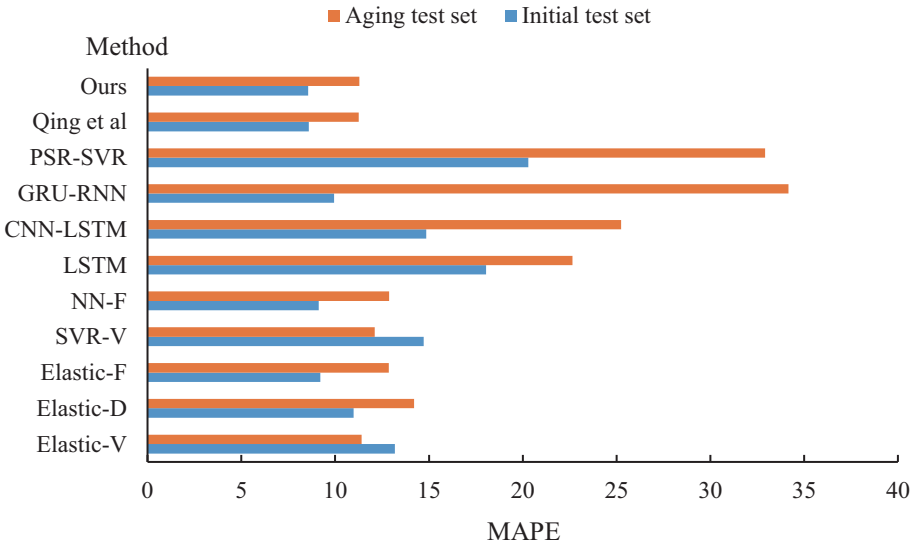

FIGURE 7. Different algorithm MAPE varies.

that selecting appropriate domain knowledge features for the model is essential. It also shows that simple models (e.g., Elastic-V) have poor generalization ability and cannot achieve good performance on the subtest dataset. Deep neural networks (e.g., LSTM and CNN-LSTM) also performed poorly on both test sets, which is not surprising since they were initially designed to capture capacity degradation curves, a degradation process that is very weak in the early stages of battery life. The results of GRU-RNN and PSR-SVR show that in early prediction of remaining battery life, it is challenging to generate typical features from basic features (such as discharge voltage).

In this work, we use only the test set of the first 80 cycles of the power battery, and the results show that the proposed model significantly outperforms the baselines on both the initial test set and the aging test set, even though that the baseline models employ more than 100 cycles of data. The results indicate that the proposed model improves the

generalization ability and delays the effectiveness of the deterioration of the prediction results. The results show that the RMSE and MAPE values of this work outperforms those of Qing et al. [17]. The prediction accuracy and standard deviation values are better than those of the model proposed by Qing et al. [17], and the cycle number is significantly decreased by 20%.

6. **Conclusions and Future Work.** This work proposed a hybrid model based on the fusion of domain knowledge and statistics features, which owns the significant advantage of interpretability and feature extraction capability. In the model, the ECA mechanism and adaptive dropout are integrated to capture slight changes in the early stages of the battery, helping the model better handle noise and uncertainty during training and improving the stability of the prediction model. As a result, we are able to use fewer cycles to obtain more accurate RUL prediction results, reduce over-reliance on specific samples, and improve the generalization.

Although the experimental results improve in terms of accuracy and generalization, the domain knowledge features in this work are usually designed for specific battery types and specific operating conditions. These features must be recalibrated or remodeled when the battery type or operating conditions change. Therefore, it will be crucial to integrate electrochemical, thermal, and mechanical information into RUL predictions as it can be better adapted to real-world application scenarios. In addition, it will be crucial to investigate the application of RUL algorithms to promote the reuse of retired power batteries to protect the environment.

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REFERENCES

[1] T.-Y. Wu, X. Guo, Y.-C. Chen, S. Kumari, and C.-M. Chen, "Sgxap: Sgx-based authentication protocol in iov-enabled fog computing," *Symmetry*, vol. 14, no. 7, p. 1393, 2022.

[2] T.-Y. Wu, Z. Lee, L. Yang, J.-N. Luo, and R. Tso, "Provably secure authentication key exchange scheme using fog nodes in vehicular ad hoc networks," *The Journal of Supercomputing*, vol. 77, pp. 6992–7020, 2021.

[3] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to rul prediction," *Mechanical Systems and Signal Processing*, vol. 104, pp. 799–834, 2018.

[4] C. Hu, G. Jain, P. Tamirisa, and T. Gorka, "Method for estimating capacity and predicting remaining useful life of lithium-ion battery," in *2014 International Conference on Prognostics and Health Management*. IEEE, 2014, pp. 1–8.

[5] B. Saha, K. Goebel, and J. Christophersen, "Comparison of prognostic algorithms for estimating remaining useful life of batteries," *Transactions of the Institute of Measurement and Control*, vol. 31, no. 3-4, pp. 293–308, 2009.

[6] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 5695–5705, 2018.

[7] Y. Zhang, R. Xiong, H. He, and P. et al., "Lithium-ion battery remaining useful life prediction with box–cox transformation and monte carlo simulation," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 2, pp. 1585–1597, 2018.

[8] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, and D. Fraggedakis, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy*, vol. 4, no. 5, pp. 383–391, 2019.

[9] P. M. Attia, A. Bills, F. B. Planella, P. Dechent, G. Dos Reis, M. Dubarry, P. Gasper, R. Gilchrist, S. Greenbank, and D. Howey, ""knees" in lithium-ion battery aging trajectories," *Journal of The Electrochemical Society*, vol. 169, no. 6, p. 060517, 2022.

[10] X. Zheng and H. Fang, "An integrated unscented kalman filter and relevance vector regression approach for lithium-ion battery remaining useful life and short-term capacity prediction," *Reliability Engineering & System Safety*, vol. 144, pp. 74–82, 2015.

[11] T. F. Fuller, M. Doyle, and J. Newman, "Simulation and optimization of the dual lithium ion insertion cell," *Journal of the Electrochemical Society*, vol. 141, no. 1, p. 1, 1994.

[12] K. Liu, Y. Gao, C. Zhu, K. Li, M. Fei, C. Peng, X. Zhang, and Q.-L. Han, "Electrochemical modeling and parameterization towards control-oriented management of lithium-ion batteries," *Control Engineering Practice*, vol. 124, p. 105176, 2022.

[13] C.-M. Chen, Q. Miao, S. Kumari, M. K. Khan, and J. J. Rodrigues, "A privacy-preserving authentication protocol for electric vehicle battery swapping based on intelligent blockchain," *IEEE Internet of Things Journal*, 2024.

[14] C.-M. Chen, L. Chen, Y. Huang, S. Kumar, and J. M.-T. Wu, "Lightweight authentication protocol in edge-based smart grid environment," *EURASIP Journal on Wireless Communications and Networking*, vol. 2021, pp. 1–18, 2021.

[15] Y. Peng, Y. Xu, D. Liu, and J. Li, "Locality structure preserving based feature selection for prognostics," *Intelligent Data Analysis*, vol. 19, no. 3, pp. 659–682, 2015.

[16] J. Wu, C. Zhang, and Z. Chen, "An online method for lithium-ion battery remaining useful life estimation using importance sampling and neural networks," *Applied Energy*, vol. 173, pp. 134–140, 2016.

[17] Q. Xu, M. Wu, E. Khoo, Z. Chen, and X. Li, "A hybrid ensemble deep learning approach for early prediction of battery remaining useful life," *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 1, pp. 177–187, 2023.

[18] X. Hu, L. Xu, X. Lin, and M. Pecht, "Battery lifetime prognostics," *Joule*, vol. 4, no. 2, pp. 310–346, 2020.

[19] Q. Xu, M. Wu, E. Khoo, Z. Chen, and X. Li, "A hybrid ensemble deep learning approach for early prediction of battery remaining useful life," *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 1, pp. 177–187, 2023.

[20] Z. Pang, X. Si, C. Hu, and Z. Zhang, "An age-dependent and state-dependent adaptive prognostic approach for hidden nonlinear degrading system," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 5, pp. 907–921, 2021.

[21] I. Bloom, B. Cole, J. Sohn, S. A. Jones, E. G. Polzin, V. S. Battaglia, G. L. Henriksen, C. Motloch, R. Richardson, and T. Unkelhaeuser, "An accelerated calendar and cycle life study of li-ion cells," *Journal of Power Sources*, vol. 101, no. 2, pp. 238–247, 2001.

[22] M. Broussely, S. Herreyre, P. Biensan, P. Kasztejna, K. Nechev, and R. Staniewicz, "Aging mechanism in li ion cells and calendar life predictions," *Journal of Power Sources*, vol. 97, pp. 13–21, 2001.

[23] D. Liu, Y. Luo, J. Liu, Y. Peng, L. Guo, and M. Pecht, "Lithium-ion battery remaining useful life estimation based on fusion nonlinear degradation ar model and rpf algorithm," *Neural Computing and Applications*, vol. 25, pp. 557–572, 2014.

[24] R. Rouhi Ardeshiri and C. Ma, "Multivariate gated recurrent unit for battery remaining useful life prediction: A deep learning approach," *International Journal of Energy Research*, vol. 45, no. 11, pp. 16 633–16 648, 2021.

[25] W. He, N. Williard, M. Osterman, and M. Pecht, "Prognostics of lithium-ion batteries based on dempster–shafer theory and the bayesian monte carlo method," *Journal of Power Sources*, vol. 196, no. 23, pp. 10 314–10 321, 2011.

[26] C. Lyu, Q. Lai, T. Ge, H. Yu, L. Wang, and N. Ma, "A lead-acid battery's remaining useful life prediction by using electrochemical model in the particle filtering framework," *Energy*, vol. 120, pp. 975–984, 2017.

[27] Z. Liu, G. Sun, S. Bu, J. Han, X. Tang, and M. Pecht, "Particle learning framework for estimating the remaining useful life of lithium-ion batteries," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 2, pp. 280–293, 2016.

[28] X. Su, S. Wang, M. Pecht, L. Zhao, and Z. Ye, "Interacting multiple model particle filter for prognostics of lithium-ion batteries," *Microelectronics Reliability*, vol. 70, pp. 59–69, 2017.

[29] X. Zhang, Q. Miao, and Z. Liu, "Remaining useful life prediction of lithium-ion battery using an improved upf method based on mcmc," *Microelectronics Reliability*, vol. 75, pp. 288–295, 2017.

[30] Y. Chang, H. Fang, and Y. Zhang, "A new hybrid method for the prediction of the remaining useful life of a lithium-ion battery," *Applied Energy*, vol. 206, pp. 1564–1578, 2017.

[31] Y. Song, D. Liu, C. Yang, and Y. Peng, "Data-driven hybrid remaining useful life estimation approach for spacecraft lithium-ion battery," *Microelectronics Reliability*, vol. 75, pp. 142–153, 2017.

[32] J. Yu, "State of health prediction of lithium-ion batteries: Multiscale logic regression and gaussian process regression ensemble," *Reliability Engineering & System Safety*, vol. 174, pp. 82–95, 2018.

[33] D. Chen, W. Hong, and X. Zhou, "Transformer network for remaining useful life prediction of lithium-ion batteries," *IEEE Access*, vol. 10, pp. 19 621–19 628, 2022.

[34] D. Liu, Y. Luo, J. Liu, Y. Peng, L. Guo, and M. Pecht, "Lithium-ion battery remaining useful life estimation based on fusion nonlinear degradation ar model and rpf algorithm," *Neural Computing and Applications*, vol. 25, pp. 557–572, 2014.

[35] Q. Wang, B. Wu, P. Zhu, P. Li, W. Zuo, and Q. Hu, "Eca-net: Efficient channel attention for deep convolutional neural networks," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 11 534–11 542.

[36] J. Ba and B. Frey, "Adaptive dropout for training deep neural networks," *Advances in Neural Information Processing Systems*, vol. 26, pp. 3084–3092, 2013.

[37] C. Weng, Y. Cui, J. Sun, and H. Peng, "On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression," *Journal of Power Sources*, vol. 235, pp. 36–44, 2013.

[38] X. Zhang, Q. Miao, and Z. Liu, "Remaining useful life prediction of lithium-ion battery using an improved upf method based on mcmc," *Microelectronics Reliability*, vol. 75, pp. 288–295, 2017.

[39] G. Ma, Y. Zhang, C. Cheng, B. Zhou, P. Hu, and Y. Yuan, "Remaining useful life prediction of lithium-ion batteries based on false nearest neighbors and a hybrid neural network," *Applied Energy*, vol. 253, p. 113626, 2019.

[40] L. Chen, Y. Zhang, Y. Zheng, X. Li, and X. Zheng, "Remaining useful life prediction of lithium-ion battery with optimal input sequence selection and error compensation," *Neurocomputing*, vol. 414, pp. 245–254, 2020.