Prediction of Lithium-ion Battery's Remaining Useful Life Based on Multi-kernel Support Vector Machine with Particle Swarm Optimization

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Abstract

The Remaining Useful Life (RUL) of Lithium-ion (Li-ion) batteries estimation is very important for the intelligent Battery Management System (BMS). With the arrival of the era of big data, data mining technology is becoming more and more mature, and the Li-ion batteries RUL estimation based on data-driven prognostics is more accurate. However, the Support Vector Machine (SVM) applying to predict the Li-ion batteries RUL uses the traditional single radial basis kernel function, this single radial basis kernel function classifier is weak in generalization ability, and it is easy to appear the problem of data migration, which leads to the inaccurate prediction of Li-ion batteries RUL.

In this work, a novel Multi-kernel SVM (MSVM) based on polynomial kernel and radial basis kernel function is proposed. Moreover, the Particle Swarm Optimization (PSO) algorithm is used to search the kernel parameters, penalty factor and weight coefficient of the MSVM model. Finally, this paper makes use of the NASA battery data set to form the observed data sequence for regression prediction, the calculation results show that the improved algorithm not only has better prediction accuracy and stronger generalization ability, but also decreases the training time and computational complexity.

Key words: Lithium-ion batteries RUL，Multi-kernel Support Vector Machine，Particle Swarm Optimization algorithm，prediction

I. INTRODUCTION

Environmental issues triggered by emissions from conventional vehicles have accelerated the adaptation of electric vehicles (EVs) for urban transportation [1]. Lithium-ion (Li-ion) batteries have been widely used in a lot of new energy systems because of as a power source with high energy density, long service life and low pollution. Li-ion batteries are the energy of many devices, and they are quickly becoming the most common power source for EVs [2]. Remaining Useful Life (RUL) of the Li-ion battery is defined as the useful life left on the Li-ion battery at a particular time of operation. Li-ion batteries RUL estimation is essential to the Prognostics and Health Management (PHM) [3]. The batteries are subjected to physical and chemical degradation during their operations. The main factors of degradation are related to electrode corrosion and degradation of electrolyte. Some methods for estimating or calculating the battery state of health are developed [4,5,6].

In recent years, many researches have been made on the degradation model and the prediction of Li-ion batteries RUL. In order to improve the accuracy of the RUL prediction, a variety of techniques and methods are proposed to predict the Li-ion battery RUL. And these techniques and methods can be divided into two categories: model-based prognostics and data-driven prognostics.

For model-based prognostics, it requires a deeply understanding of the composition of the model, which uses mathematical expressions to describe the complex electrochemical process. And it is difficult to explicit analytical solutions because the model is always non-linear. Lumped-element equivalent-circuit components such as resistors and capacitors are used to represent the behavior of a battery cell [7]. Many works use Kalman filtering with electro-chemical or electrical equivalent-circuit models for monitoring, e.g. Refs. [8,9]. With the development of the measurement technology and reduced cost, Electrochemical Impedance Spectroscopy (EIS), a non-invasive method, has been used to characterize the battery capacity degradation through variations of the internal parameters. [10]. In Ref. [11], a method is presented for remaining useful life (RUL) estimation of lithium-ion batteries based on the internal resistance growth model using the particle filtering (PF) approach. A model-based Bayesian approach is proposed in Ref. [12] to predict remaining useful life (RUL) for these types of batteries.

For data-driven prognostics, it takes the Li-ion battery as a black box without figuring out complex electrochemical process in the model. The only work needed to do is to find out mathematical laws between the Li-ion battery historical data，then using these laws to predict the capacity or the RUL of Li-ion batteries. And the algorithms or related parameters are the main factor affecting the accuracy of RUL prediction.

Compared with the model-based prognostics, the data-driven prognostics do not need to study the battery model directly, and it believes that all information about Li-ion batteries has been fully reflected in the collected data. And the information of the battery is obtained through the analysis of the data. The data-driven prognostics can obtain the implicit information between the input and output through the training samples, and finally forecast the future trend. In the background of big data analysis, the data-driven prognostics have a good value for the prediction of Li-ion batteries RUL.

With the rapid development of machine learning technology and artificial intelligence (AI), more and more algorithms are used to predict Li-ion batteries RUL. For example, a data-driven approach for RUL prediction of Li-ion batteries using an improved Auto Regressive (AR) model by Particle Swarm Optimization (PSO) is proposed in Ref. [13]. A data-driven approach which combines Empirical Mode Decomposition (EMD) and Auto Regressive Integrated Moving Average (ARIMA) model is proposed for RUL prognostic in Ref. [14]. In Ref. [15], a data-driven method is developed using Unscented Kalman Filter (UKF) with Relevance Vector Regression (RVR), which is employed to RUL and short-term capacity prediction of batteries. An intelligent prognostic for battery health based on sample entropy feature of discharge voltage is proposed in Ref. [16]. Similarly, Particle Filter (PF) was used for predicting RUL and time until end of discharge voltage of the Li-ion battery in Ref. [17]. In Ref. [18], a multistep-ahead prediction model based on the mean entropy and Relevance Vector Machine (RVM) is developed, and applied to State of Health (SOH) and RUL prediction of the battery. An optimized RVM algorithm is utilized to improve the accuracy and stability of RUL estimation in Ref. [19]. In Ref. [20], a method for real-time RUL estimation of Li-ion batteries is proposed that integrates classification and regression attributes of Support Vector (SV) based machine learning technique. A method for estimating the battery SOH using health condition parameters by Support Vector Regression-Particle Filter (SVR-PF) was proposed in Ref. [21], which has provided a good foundation for multi-step ahead prediction. An online approach using feed forward neural network (FFNN) and importance sampling (IS) is presented to estimate Li-ion battery RUL in Ref. [22]. In Ref. [23] a novel RUL prediction method based on the Gaussian Process Mixture (GPM) is proposed, which can process multimodality by fitting different segments of trajectories with different Gaussian Process Regression (GPR) models separately, such that the tiny differences among these segments can be revealed. In Ref. [24], a novel PF-based method for RUL estimation of Li-ion batteries is developed combining Kalman filter and Particle Swarm Optimization (PSO). An Improved Unscented Particle Filter (IUPF) method is proposed for Li-ion battery RUL prediction based on Markov Chain Monte Carlo (MCMC) in Ref. [25], which uses the MCMC to solve the problem of sample impoverishment in Unscented Particle Filte (UPF) algorithm. A new data-driven prognostic method is proposed based on the Interacting Multiple Model Particle Filter (IMMPF) for determining the Li-ion batteries RUL and the Probability Distribution Function (PDF) of the associated uncertainty in Ref. [26].

For the estimation of SOH and RUL, one of the most powerful and popular machine learning algorithms, the Support Vector Machine (SVM), is combined with a completely new method for data processing [27], which can handle nonlinear systems, outperform ordinary regression due to its insensitivity to small changes. Besides, the performance of SVM does not directly depend on the dimension of classified entities [28].

SVM is popular in many fields, such as financial time series and power load forecasting. The selection and construction of kernel functions is crucial when using SVM to predict RUL of Li-ion batteries, which have great influence on the efficiency and generalization performance of Li-ion batteries RUL prediction. And the way of training sample selection will also affect the quality of Li-ion batteries RUL prediction. The existing kernel function for Li-ion batteries RUL prediction based on SVM is the single kernel function. In Refs.[18,29,30], they all use a single kernel function, without considering the shortcomings of the single kernel function. Under certain conditions, the single kernel function shows some learning and generalization ability. However, the construction of kernel function and the selection of related parameters have not been well set up. Several basic forms of kernel functions are often used with different mapping properties, which show great performance differences in different applications. It is not reasonable to use only single kernel function when using SVM to predict Li-ion batteries RUL. In view of this, in order to solve the limitations of SVM algorithm in the application of Li-ion batteries RUL prediction and make the prediction more accurate, this study introduces a novel Multi-kernel SVM with Particle Swarm Optimization（PSO-MSVM）algorithm.

In this contribution, it utilizes the data-driven methods to make prediction of Li-ion batteries RUL with PSO-MSVM, which not only makes the prediction more accurate, but also decreases the training time and computational complexity. The remaining parts of this article are arranged as follows: Section 2 introduces the concept of SVM and MSVM algorithm. A practical optimized method is proposed in Section 3 to carry out the global optimal search on the key parameters, and further improves the prediction accuracy and the calculation speed of the MSVM model. Then, this paper verifies the PSO-MSVM algorithm based on NASA battery data in Section 4 and makes an analysis of the prediction results. Finally, a summary of the full paper is given in Section 5.

II. MULTI-KERNEL SVM LEARNING ALGORITHM

A Support Vector Machine (SVM)

This part introduces some basic theories of SVM. The main idea of SVM is to establish an optimal separating hyper-plane as the decision plane by maximizing the distance between positive and negative examples [31, 32].

Given a training data set $Q = \{\mathbf{x}_j, y_j\}_{j=1}^{n}$, $(\mathbf{x}_j \in \mathrm{R}^n, y_j \in \mathrm{R})$, $\mathbf{x}_j$ is the j-th input feature vectors, y_j is the class label of $\mathbf{x}_j$, the number of all samples is indicated by n.

When the training sample is completed, an optimal hyper-plane can be established as follow:

$$p(\mathbf{x}) = \mathbf{w}^T \cdot \phi(\mathbf{x}) + b \quad (1)$$

In the hyper-plane (1), the function of $\phi(\mathbf{x})$ is used to map the input feature vector into high dimensional feature space, b is a bias term, $\mathbf{w}$ is a vector of the hyper-plane. The estimated values of b and $\mathbf{w}$ can be obtained by solving the following quadratic program:

$$\min \ T(\mathbf{w}, b, \varepsilon) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{j=1}^{n}\varepsilon_j \quad (2)$$

$$\text{s.t.} \ \ y_j\left(\mathbf{w}^T \cdot \phi(\mathbf{x}_j) + b\right) \geq 1 - \varepsilon_j \quad j = 1, \ldots, n \quad (3)$$

$$\varepsilon_j \geq 0 \quad j = 1, \ldots, n \quad (4)$$

The Lagrangian of the quadratic program in (2)–(4) is

$$L(\mathbf{w}, \varepsilon, b; \boldsymbol{\alpha}) = T(\mathbf{w}, \varepsilon, b) - \sum_{j=1}^{n}\alpha_j\{y_j(\mathbf{w}^T \cdot \phi(\mathbf{x}_j) + b) + \varepsilon_j - 1\} - \sum_{j=1}^{n}\mu_j\varepsilon_j \quad (5)$$

Taking partial derivatives of $L(\mathbf{w}, \varepsilon, b; \boldsymbol{\alpha})$ with respect to the primal variables and substituting the results into $L(\mathbf{w}, \varepsilon, b; \boldsymbol{\alpha})$ in (5) lead to the dual formulation of the SVM

$$\max \ \ L(\mathbf{w}, \varepsilon, b; \boldsymbol{\alpha}) = \left\{\sum_{j=1}^{n}\alpha_j - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i\, y_j K(\mathbf{x}_i, \mathbf{x}_j)\right\} \quad (6)$$

$$s.t. \ \ \sum_{j=1}^{n} y_j\, \alpha_j = 0 \quad (7)$$

$$0 \leq \alpha_j \leq C \quad j = 1, \ldots, n \quad (8)$$

In (6)–(8), α_j is the Lagrange multiplier of observation j , and the inner product function $K(\mathbf{x}_i, \mathbf{x}_j)$ is called the kernel function. By introducing the kernel function, high dimensional feature space in the inner product can implicitly operate through a kernel function of the original space.

The computation process of SVM can be simplified by transferring the problem with Kuhn-Tucker condition into the equivalent Lagrange dual problem. Therefore, the linear decision function is obtained by solving the dual optimization problem and the SVM problem can be simplified as follows:

$$p(\mathbf{x}) = \mathrm{sgn}\left(\sum_{j=1}^{n}\alpha_j y_j K(\mathbf{x}_j, \mathbf{x}) + b\right) \quad (9)$$

The SVM is not only widely used in classification problems but also has been applied in regression problems, because the regression problem is a difficult classification problem in essence. SVM has many advantages, such as good robustness, simple calculation, wide universality, and the theory is perfect.

B. Multi-kernel SVM learning algorithm

When the SVM is used to predict the Li-ion battery RUL, the selection of the kernel function of the model is very important. SVM using different kernel functions will form different prediction models, which will produce different prediction accuracy and efficiency.

The two types of kernel functions commonly used in SVM are global kernel and local kernel.

Radial Basis Function (RBF) kernel is a typical local kernel, and its mathematical form is defined as follows [33]:

$$K_{RBF}(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{1}{2\sigma^2}\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2\right) \quad (10)$$

Where σ is the parameter of the kernel.

Polynomial kernel is a typical global kernel, which is defined as follows [34]:

$$K_{poly}(\mathbf{x}_{i,}\mathbf{x}_j) = \left(\mathbf{x}_i^T\mathbf{x}_j + 1\right)^d \quad (11)$$

Where d denotes the kernel parameter.

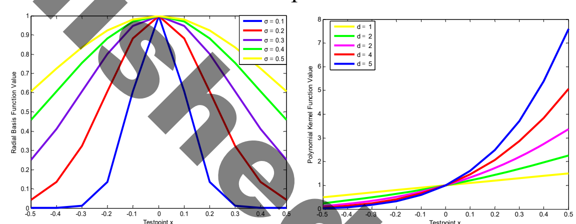

Fig 1. Curves of different test points for RBF and Polynomial kernel.

Fig.1 shows the effect of function kernel in different parameters value. From Fig.1, it can be concluded that, RBF kernel has the local characteristics, and has better learning ability; polynomial kernel function has global characteristics, and has strong generalization performance. The performance and complexity of the Li-ion battery RUL prediction model are determined by the kernel function.

Smits proposed that it is difficult to improve the performance of SVM by using only a single kernel function [35]. In this paper, a MSVM is proposed to improve the prediction accuracy and generalization ability of SVM. The kernel function of MSVM is composed of the local kernel function K_{RBF} and the global kernel function K_{poly}.

$$K_{new} = \tau K_{RBF} + (1-\tau)K_{poly} \qquad (0 < \tau < 1) \quad (12)$$

Where τ is the weight coefficient. The kernel function must satisfy Mercer's Theorem, which can be used as the kernel of SVM. Because both K_{RBF} and K_{poly} satisfy Mercer's Theorem, the multi-kernel function K_{new}, which is formed by the convex combination of them, also satisfies the Mercer theorem.

Fig.2 shows the effect of multi-kernel function for the chosen test point x = 0.2 in different parameters value τ =0.5, 0.6, 0.7, 0.8, 0.9, among which σ =0.2, d = 2. From Fig.2, it can be seen that multi-kernel function integrates all characters of traditional single kernel and has better distribution performance in different data set.

When τ approaches 0, the polynomial kernel function has a greater influence on the multi-kernel function, showing the global generalization performance of the polynomial kernel function; when the τ approaches 1, the RBF kernel has a greater influence on the multi-kernel kernel function, showing the local fitting performance of the RBF kernel. In the prediction of Li-ion batteries RUL, it must adjust the weight coefficient τ so as to the MSVM adapted to different data distribution.

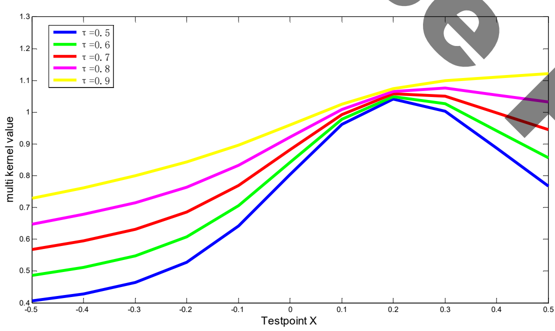

Fig. 2. The test curve of multi-kernel function.

III. PARTICLE SWARM OPTIMIZATION ALGORITHM

It can be seen from Section 2 that there are several important parameters in the MSVM model. They are C, σ, d and τ respectively. The function of the penalty constant C is to find the proper balance between separating error and computational complexity. The characteristics of training data are reflected by the kernel function σ and d. The weight coefficient τ is used to assign the weight for K_{RBF} and K_{poly}. All four parameters have a direct impact on the performance of the MSVM model. However, for a given problem, it is not known which parameters are optimal in advance. Therefore, it must optimize the parameters before training MSVM model, so that the model can accurately predict the unknown data.

Grid algorithm is used to optimize the penalty constant C and σ of RBF in Ref. [36]. However, grid algorithm has a major drawback is that feature subset cannot be selected at the same time. In Ref. [37], feature subset and model parameter selection of Support Vector Machine are optimized by Genetic Algorithm (GA).

Inspired by social behavior in nature, Particle Swarm Optimization（PSO）, proposed by Kennedy and Eberhart [38,39], is adopted to optimize the parameters of MSVM prediction model in this paper.

Similar to other evolutionary algorithms, PSO algorithm uses a particle swarm to operate. Each particle has two features: its own position and speed, and represents a solution to a problem in the decision space. The current value in the solution is represented by the position, and the direction and distance of the optimal position in the next iteration is defined by velocity.

Each particle changes its search direction based on two factors, namely its own best previous experience and its best solution in all other members to find the optimal solution [40].

Supposed in a M-dimensional space, there are n particles formed a population of $X = (X_1, X_2, \dots X_n)$. The M-dimensional position for the particle j at iteration d can be expressed as $x_j^d = \{x_{j1}^d, x_{j2}^d, \dots x_{jM}^d\}$. Likewise, the velocity, which is also a M-dimension vector, for particle j at iteration d can be expressed as $v_j^d = \{v_{j1}^d, v_{j2}^d, \dots v_{jM}^d\}$. Let $p_j^d = \{p_{j1}^d, p_{j2}^d, \dots p_{jM}^d\}$ represent the optimal solution that particle j has obtained until iteration d, and $p_g^d = \{p_{g1}^d, p_{g2}^d, \dots p_{gM}^d\}$represent the optimal solution obtained from p_d^j in the population at iteration d.

In each iteration process, the position and velocity of each particle are updated according to the individual extremum and the global extremum, and the updating formula is as follows:

$$V_{jm}^{d+1} = \gamma V_{jm}^d + c_1 r_1 \left(P_{jm}^d - X_{jm}^d\right) + c_2 r_2 \left(P_{gm}^d - X_{jm}^d\right) \quad (13)$$

$$X_{jm}^{d+1} = X_{jm}^d + V_{jm}^{d+1} \quad (14)$$

where γ is the inertia weight; $m = 1,2,\dots,M$; d is the current iteration; c_1 and c_2 are constants called acceleration coefficients; r_1 and r_2 are random numbers, which obey the Uniform Distribution (0,1); X_{jm}^d represents the previous position and its value is limited within the interval $[-X_{max}, X_{max}]$; V_{jm}^d indicates the previous velocity, which is limited within the interval of $[-V_{max}, V_{max}]$.

The basic process of the PSO algorithm mainly comprised five steps: Initialization, Evaluate the fitness, Update particle velocity, Construction, and Stopping Criteria. Each step is defined as follow:

The basic process of the PSO algorithm

STEP1. (Initialization) Initialize population positions and velocities randomly.

STEP2. (Evaluate the fitness) Evaluate the fitness of each particle.

STEP3. (Update particle velocity) Calculate the velocity of each particle in the population according to formula (13).

STEP4. (Construction) Calculate the next position of each particle according to the formula (14).

STEP5. (Stopping Criteria) If the stopping criterion is satisfied, stop the PSO algorithm, otherwise return STEP2.

The sign of the end of the iteration is that the number of iterations has reached the maximum numbers of iterations which was set in advance.

To make it more clear to understand the idea of PSO algorithm, the computation flowchart is illustrated in Fig. 3.

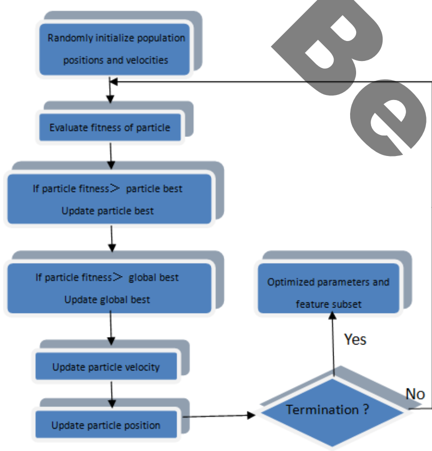

Fig. 3. The flowchart of PSO algorithm.

IV. PSO-MSVM FOR LI-ION BATTERIES RUL ESTIMATION

Based on the above analysis，the principle of PSO-MSVM algorithm can be obtained, as shown in the flowchart of Fig. 4.

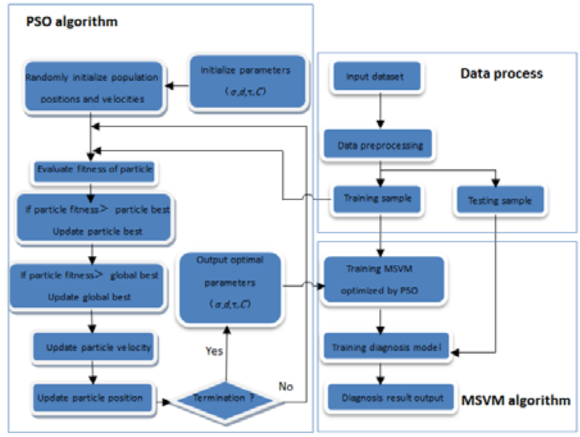

Fig. 4. The flowchart of PSO-MSVM algorithm.

A Feature extraction and selection

It is necessary to find the operational parameters that change with the Li-ion battery aging to give a good indication of the Li-ion battery SOH. The accuracy of the Li-ion battery health estimation and RUL prediction will heavily rely on these so called features [41]. From the raw data of the Li-ion battery from NASA, a large number of features can be extracted, but not all of the features are associated with the RUL of Li-ion batteries. Up to now, several features have been extracted from three different conditions (charge, discharge, and impedance).

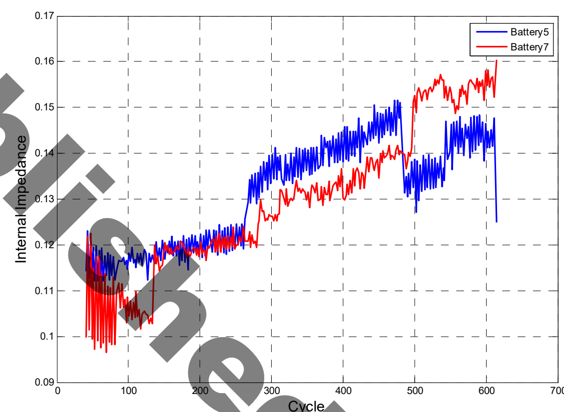

Fig. 5. The Internal Impedance change curve of No.5 and No.7 batteries

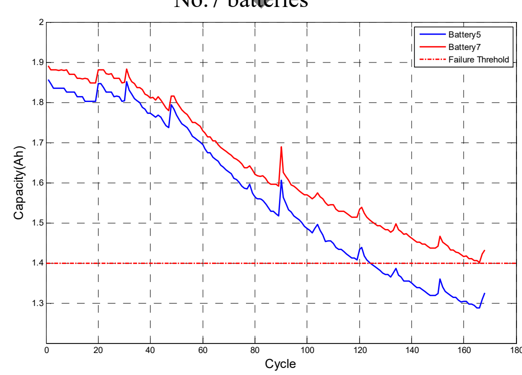

Fig.6.The capacity change curve of No.5 and No.7 batteries.

Although the impedance data is accurate, it is difficult to be collected in a practical application [35]. Because the battery must be isolated from the application and it must use the electrochemical impedance spectroscopy (EIS) to measure the AC current. Although the impedance data can be given by the NASA (see Fig.5), but from a technical point of view, the impedance data are difficult to be collected online. What's more, the measurement of the internal impedance of the Li-ion battery requires a battery model, and the choice of the model directly affects the accuracy of the battery internal resistance data. The internal impedance measured by the battery model is used to predict the Li-ion battery RUL, which will greatly reduce the prediction accuracy. Therefore, in this paper, it cannot be used to predict the Li-ion battery RUL.

As can be seen from Fig. 6 that the capacity change curve of No.5 and No.7 batteries in discharge cycles are consistent. The Li-ion battery capacity refers to the amount of current that can be supplied by the Li-ion battery over time. During the charging and discharging cycles of Li-ion batteries, the capacity is decaying over time, which is a good way to measure the health of the Li-ion battery. In the capacity decay process of Li-ion batteries, there are some spikes; these spikes are rest periods of varying lengths where the capacity appears to increase because the battery test bed has time to get rebalanced [41]. However, these spikes do not affect the prediction of the Li-ion battery RUL. Thanks to the information of capacity in the use of the process has a very consistent trend, this paper will use the capacity as a feature for Li-ion batteries RUL estimation.

When using PSO-MSVM algorithm to train the Li-ion battery data，data feature extraction and selection directly affects the accuracy of prediction. It can be clearly seen from Fig. 7 that the discharging voltage curve of each discharge cycle is different. This study selects 500s, 1000s, 1500s, 2000s voltage values of each discharge cycle as input data sequence, and the corresponding capacity of each discharge cycle as the output.

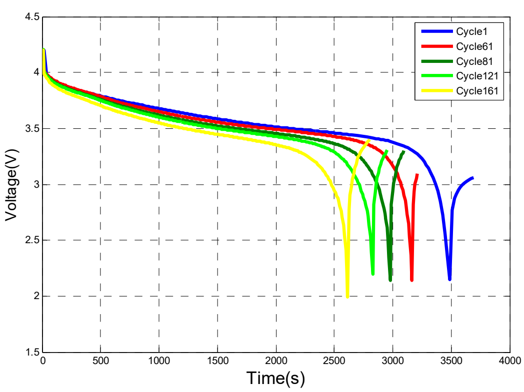

Fig. 7. Voltage curves of different discharge cycles.

B. Li-ion batteries RUL prediction

The Li-ion battery data used in this paper are obtained from the NASA Prognostics Center of Excellence (PCoE)[42], which uses a battery prediction test bench and 18650 rechargeable batteries sold on the market to collect battery charge and discharge data[43]. The Li-ion batteries operate at room temperature in three different operating conditions: charge, discharge and full impedance respectively.

Charge mode: Charging was implemented in the case of constant current mode at 1.5A until the battery voltage reached 4.2V, then maintained a constant voltage mode until the charge current is reduced to 20 mA.

Discharge mode: Discharging was conducted at a constant current level of 2A until the battery voltage dropped to 2.7V and 2.2V for batteries No.5 and No.7, respectively.

Repeated charge / discharge cycles are the main causes of accelerated fading of the battery. When Li-ion batteries are up to 30% rated capacity aging (this experiment is from 2Ah to 1.4Ah), the experiments were stopped and Li-ion batteries are considered to have reached the end of life.

In the NASA Li-ion batteries data, this paper extracts the data from the discharge cycle of Li-ion batteries to validate our algorithm. The data is divided into two parts, the first part is used to train the model, and the other is used to test the model

This paper makes the following definitions: RSVM refers to the SVM algorithm with RBF kernel, PSVM refers to the SVM algorithm with Polynomial kernel, MSVM refers to the SVM algorithm Multi-kernel expressed by Equation (12) and PSO-MSVM refers to MSVM optimized by the PSO algorithm.

To verify the superiority of PSO-MSVM, this paper will be described from the following two aspects:

Firstly, this paper uses different numbers of training data to train RSVM, PSVM, MSVM and PSO-MSVM, respectively.

Secondly, it compares the prediction accuracy of RSVM, PSVM, MSVM and PSO-MSVM under the same training data.

As can be seen from Fig. 6 that the actual end of the lifetime of battery No.5 is cycle 168, but at this point the capacity of battery No.7 has not dropped to the failure threshold. Then, this study focuses on the RUL prediction for the former and the capacity estimation for the latter, respectively. All of them can verify the predictive ability of these algorithms. To verify the accuracy of the proposed model for predicting the Li-ion batteries RUL, the samples 1~80, 1~112 are chosen as the training data set, and the corresponding sample 81~168,113~168 is used to predict the validation. When the remaining capacity of battery reaches the threshold, it believes that the end of the lifetime of the battery.

Fig.8 and Fig.9 are prediction of the battery No.5 RUL under different training samples, and they also show the predicted results of RSVM, PSVM, MSVM and PSO-MSVM.

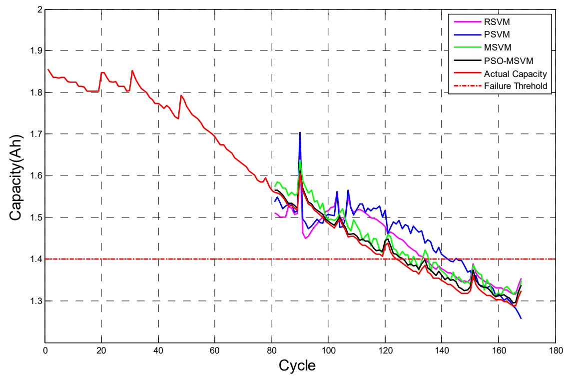

Fig 8. Predicted results of RSVM, PSVM, MSVM and PSO-MSVM using 80 sets of training data (Battery No.5).

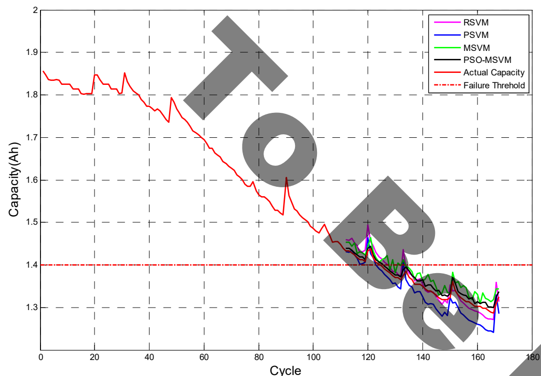

Fig 9. Predicted results of RSVM, PSVM, MSVM and PSO-MSVM using 112 sets of training data (Battery No.5).

For battery No.5, this paper defines:

$$AE = |RUL - PRUL| \tag{15}$$

$$RE = \frac{|RUL-PRUL|}{RUL} \times 100\% \tag{16}$$

Where RUL represents the real RUL value and $PRUL$ represents the predicted RUL value, all of which are the indexes of prediction performance. TS refers to number of training samples. Table1 shows the comparison of calculation results of SVM between different kernel function.

TABLE I
COMPARISON OF CALCULATION RESULTS OF SVM BETWEEN DIFFERENT KERNEL FUNCTION (BATTERY No.5)

Kernel function	TS	RUL	$PRUL$	AE	RE/%
RSVM	80	44	56	12	27.28
	112	12	15	3	25.00
PSVM	80	44	62	18	40.91
	112	12	8	4	33.33
MSVM	80	44	49	5	11.36
	112	12	13	1	8.33
PSO-MSVM	80	44	46	2	4.55
	112	12	12	0	0

From Figs.8–9 and Table1, it is clear that RE of PSO-MSVM is much smaller than that of RSVM, PSVM and MSVM with the same TS. For example, with the TS of cycle 80, RE of PSO-MSVM is 4.55%, while RE of RSVM, PSVM and MSVM is 27.28%, 40.91% and11.36%, respectively. Thereby it can make a conclusion that PSO-MSVM has better performance in prediction, the errors of which are all less than 5% with different the TS.

Fig.10 and Fig.11 are the capacity estimation of the battery No.7 under different training samples, and they also show the predicted results of RSVM, PSVM, MSVM and PSO-MSVM.

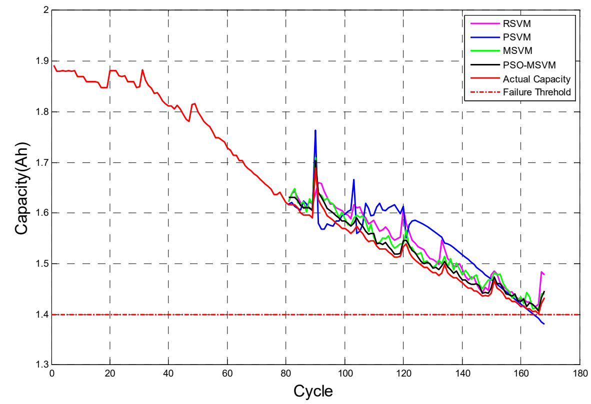

Fig 10. Predicted results of RSVM, PSVM, MSVM and PSO-MSVM using 80 sets of training data (Battery No.7).

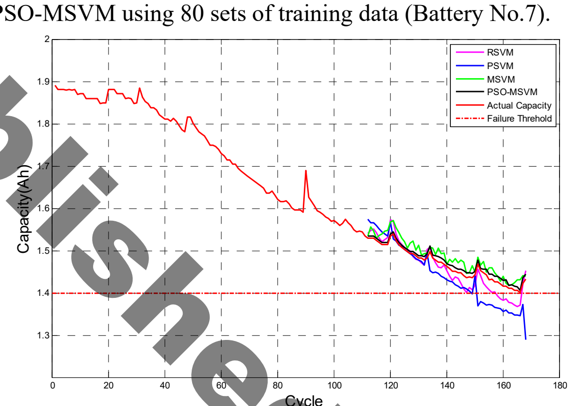

Fig 11. Predicted results of RSVM, PSVM, MSVM and PSO-MSVM using 112 sets of training data (Battery No.7).

For battery No.7, this paper defines:

$$MSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - py_i)} \tag{17}$$

Where y_i represents the true capacity value and py_i represents the forecast capacity value. TS refers to number of training samples. CC refers to Correlation coefficient. OT refers to the operating time of the prediction algorithm. Table2 shows the comparison of calculation results of SVM between different kernel function.

TABLE II
COMPARISON OF CALCULATION RESULTS OF SVM BETWEEN DIFFERENT KERNEL FUNCTION (BATTERY No.7)

Kernel function	*TS*	*CC*	*MSE*	*OT/ms*
RSVM	80	0.8921	0.0313	413.16
	112	0.9136	0.0271	503.21
PSVM	80	0.8703	0.0408	475.28
	112	0.8990	0.0395	567.15
MSVM	80	0.9535	0.0263	390.68
	112	0.9796	0.0231	458.54
PSO-MSVM	80	0.9811	0.0213	310.36
	112	0.9902	0.0154	350.25

From Figs. 10–11 and Table 2, it can be seen that *CC* of PSO-MSVM is much larger than that of RSVM, PSVM and MSVM with the same *TS*. For example, with the *TS* of cycle 112, *CC* of PSO-MSVM is 0.9902, while *CC* of RSVM, PSVM and MSVM is 0.9136, 0.8990 and 0.9796 respectively. And the *MSE* of PSO-MSVM is much smaller than that of RSVM, PSVM and MSVM with the same TS. For example, with the *TS* of cycle 80, *MSE* of PSO-MSVM is 0.0213, while CC of RSVM, PSVM and MSVM is 0.0313, 0.0408 and 0.0263 respectively. What's more, the operating time of PSO-MSVM is shorter than that of RSVM, PSVM and MSVM. So it can be concluded that PSO-MSVM model performs better than other models in the Li-ion battery RUL prediction and the capacity estimation.

By comparing Fig.8 and Fig.10, Fig.9 and Fig.11 , it can be seen clearly when using RSVM and PSVM to make a forecast for Li-ion batteries RUL of the different data set, they all show a very poor robustness; while MSVM and PSO-MSVM show a very good robustness.

In short, PSO-MSVM has better prediction accuracy and stronger generalization ability, and it can also reduce the training time and computational complexity.

V. CONCLUSIONS

The main contributions of this paper can be summarized as follows:

To solve the problem that Li-ion batteries RUL is difficult to predict, this paper proposes a PSO-MSVM model. The advantages of global kernel and local kernel functions are fully considered in this model. In this study, a MSVM is constructed by using the convex combination of RBF kernel and Polynomial kernel, and the PSO algorithm is adopted to optimize the parameters of MSVM model. Then this paper trains PSO-MSVM model by using the Li-ion battery data from NASA PCoE. And the trained model is used to predict the capacity and RUL of Li-ion batteries. By comparing the above forecast results among RSVM, PSVM, MSVM and PSO-MSVM, it shows that the proposed method has better prediction performance than these traditional single kernel support vector machine in Li-ion batteries RUL prediction and the capacity estimation.

Compared with conventional single kernel SVM, PSO-MSVM model has better prediction accuracy and strong generalization performance in different situations, and the *MSE* is less than 3%. Moreover, PSO-MSVM model can also reduce the training time and computational complexity. The method proposed in this study can provide reliable data for the BMS and other safety systems, and can accurately predict the Li-ion battery RUL.

The future work of this study is to make the PSO-MSVM model more accurate and more efficient. In addition, efforts will be made toward the structure of the kernel function with three kernel function. What's more, the next important work is to carry out experiments to collect the realistic data sets of the Li-ion battery of EVs, and the realistic data sets will be used to verify the efficient of the PSO-MSVM model.

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