Fault Prediction of Electromagnetic Launch System Based on Knowledge Prediction Time Series

Lu Junyong, Tang Yinyin, Zeng Delin, Yan Feifei, and Zheng Yufeng

***Abstract*—The fault prediction of the electromagnetic launch (EML) system is an important guarantee to improve the reliability of the system, but there is no mature method that can be directly applied. Combined with the engineering practice of large-scale EML system, a fault prediction method based on knowledge prediction time series is proposed. First, the high-frequency waveform collected in each launch is extended into a time series along the number of launches; second, an intelligent waveform features extraction expert system is constructed to realize feature extraction; third, multidimensional feature sequence prediction and waveform prediction are realized by using two neural networks, respectively; finally, fault prediction is realized by associating the fault diagnosis knowledge. The temperature rising test data of a railgun system for 15 consecutive launches and the recoil stroke test data of noncontinuous 78 launches are used as the input source of the proposed algorithm. The results show that the proposed algorithm can automatically extract the features with fault trend. The single step prediction error of features is less than 1.47%, and the mean square error of curve prediction is half of the results of SARIMA prediction algorithm. Through the temperature rise curves, the proposed algorithm can predict the fault free of the 14th and 15th launch. According to the recoil stroke curves, the fault of the launcher of the 75th launch is predicted. The actual analysis shows that the fault prediction accuracy is high, and the algorithm can significantly improve the system reliability after being applied to engineering.**

***Index Terms*—Electromagnetic launch (EML) system, expert system, fault prediction, health monitoring, neural network, time series prediction.**

I. Introduction

With the development of electromagnetic launch (EML) technology, the mode of operation is gradually changing from chemical energy to electromagnetic energy [1], [2]. In the last 10 years, there have been carrier EML systems [3], large-scale railguns [4], electromagnetic coil guns [5], and so on. Compared with the traditional complex electrical system, the biggest difference of EML system is its nonperiodic transient pulse operating mode. In the nonworking state, the system has no energy flow. When the EML task starts, it needs to complete the transformation and transfer of more than 100 megajoules of electric energy in a few seconds, and feed tens of GW of super power into the launcher in tens of milliseconds to accelerate the projectile to ultra-high speed [6]. During the launching process, most of the components of the system are in adverse working condition, and the large instantaneous power aggravates the failure rate and damage of the system [7]. At present, the development of large-scale EML system is still in the stage of function expansion [1], while the research on fault prediction of the system is very few.

Fault prediction technology is one of the most difficult technologies in the health monitoring of complex systems. At present, there are mainly three kinds of fault prediction methods: one is the method based on probability statistical model [8], [9]. Through a large number of failure data probability statistics, the probability estimation of possible failure is obtained, and the failure prediction is realized. This method needs a lot of fault sample data, but the current fault data of EML system is very few and biased. The second is the method based on the accurate failure model [10], [11]. Through the establishment of accurate failure analysis model and a large number of life test data, the failure analysis mathematical model of components or systems is established to predict the failure. It is difficult to establish accurate failure model for EML system with multi physical fields coupled and short time and high dynamic reasons. The third is the prediction method based on time series [12], [13]. The core of this technology is to find the time series which can reflect the degradation trend of system performance, and then use the time series prediction technology to predict the future value of the series and predict the fault. It is found that the EML system is suitable for the application of the third method, but its specific implementation process needs careful design.

Many high sampling rate waveforms can be collected in each EML process. Although the launch intervals are not consistent, the time series about the launch times can be obtained by taking the launch times as the time axis. It is found that, with the decline of system health, the collected waveform will change slightly, and the time of system failure can be predicted by identifying and predicting these changes. Therefore, the method of time series prediction can be used to predict system faults.

The general steps of system fault prediction based on time series prediction include: 1) discovering the expert knowledge of the relationship between time series and fault, 2) accurately

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predicting the future waveform of time series, and 3) using the existing fault knowledge to diagnose the fault from the predicted waveforms. The application of this method in EML system needs to overcome the following problems:

1) It is difficult to accurately predict the time series of EML system. The EML time series is an aperiodic instantaneous pulse series, and the change of each launch waveform is often not a feature but a combination of many features, and the known launch times are limited. All of the traditional prediction methods [14]–[16] (such as ARMA [14], neural network [15], support vector machine [16], etc.) cannot solve above problems. SARIMA [17] (seasonal auto-regressive single integer moving average) algorithm has uniqueness for seasonal series prediction, and it is also widely used in engineering, but engineering practice shows that the effect is still poor.
2) It is difficult to find fault diagnosis expert knowledge based on waveform. So far, the publicly reported fault data of EML system is still very few, and a large number of fault knowledge has not been found. If only use the existing knowledge to predict the fault, there will be more fault omissions. Therefore, the proposed fault prediction algorithm not only can accurately predict the sequence, but also can find the fault prediction knowledge to the greatest extent, and can be used to predict the fault.

So it is urgent to put forward new targeted and effective prediction methods.

Based on the engineering practice in this field, this article proposes a combined fault prediction method based on knowledge prediction time series. First, the intelligent feature extraction expert system is constructed to extract feature set automatically; second, the feature is extended into multidimensional time series, and neural network is used to predict multidimensional feature series; third, neural network technology is applied again to restore prediction curve using the predicted feature set [18]; finally, using predict results, combined with the existing fault diagnosis knowledge, the accurate system fault prediction is completed.

The rest of this article is organized as follows. In Section II, the EML system and time series prediction analysis is described in detail. In Section III, the proposed fault prediction method of EML system based on knowledge prediction time series (FP-BKPTS) and the fault prediction framework is illustrated. The temperature rising data of the rail obtained from 15 consecutive launches test and the recoil stroke data obtained from 78 single launch tests of an electromagnetic railgun prototype are studied by the proposed method and the results analysis in detailed in Section IV. Conclusion and the contribution of the research are presented in Section V.

II. Electromagnetic Launch System and Time Series Prediction Analysis

A. Typical Electromagnetic Launch System

The typical system structure of an electromagnetic large-scale railgun system is shown in Fig. 1. The power grid first charges the energy storage system and stores the energy. During EML,

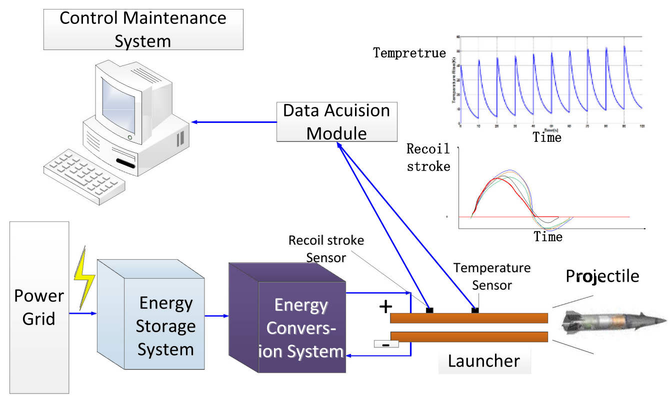

Fig. 1. Large electromagnetic railgun system topology.

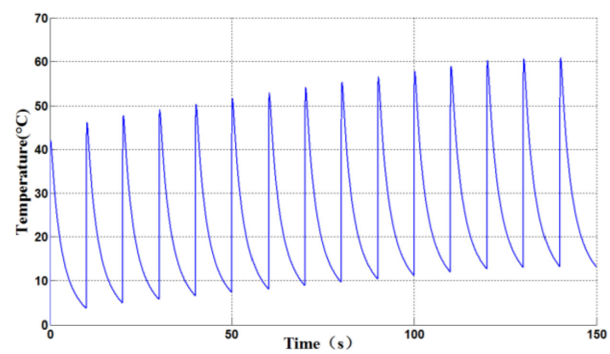

Fig. 2. Temperature rise time series of rail of 15 continuous launches.

the energy storage system quickly transfers the energy to the energy conversion system (usually pulse capacitor), and then discharges the launching device instantaneously (tens of millisecond). Through the Lorentz force generated in the projectile armature, the projectile is accelerated up to several thousand meters per second. The launch process has experienced twice energy compression, and the peak power can reach tens of GW.

In order to monitor the health status of the system, the measuring equipment shown in Fig. 1 is adopted. Many sensors are installed directly on the underlying equipment, such as a temperature sensor and recoil stroke sensor, after launch process has started, the sensor data is uploaded to the control and maintenance computer in real time through the data acquisition module, the control and maintenance system processes all data in real time, diagnoses and predicts faults quickly, and assists in decision-making to stop the launch. The implementation of the fault prediction algorithm proposed in this article is also included in the control and maintenance software.

B. Prediction Analysis of EML Time Series

Fig. 2 shows a typical EML time series. The curve has a short duration (only 150 s for 15 launches), but there are many data points (sampling rate is 100 kHz, a total of $1.5 * 10^7$ data points). The sequence shows obvious seasonality, that is, each launch is a season, the waveform is relatively similar, but the waveform of each launch has slight difference. Compared with the traditional time series prediction, the above curves are obviously different:

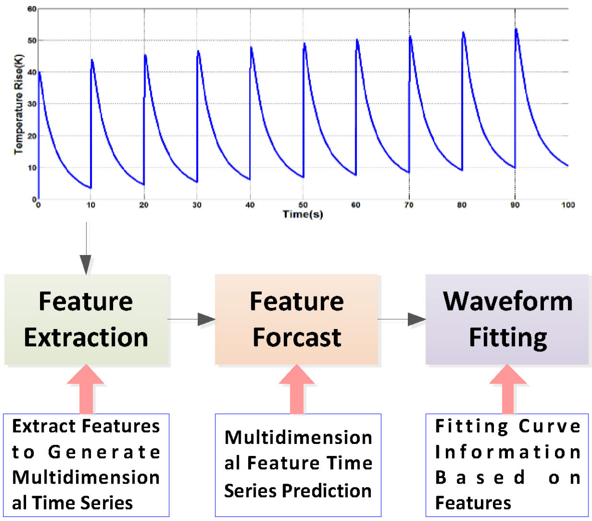

Fig. 3. Main idea of time series prediction method.

1) the time interval is less than 10 μs and there are many data points; 2) the predicted waveform is not a point but a season; 3) the nonlinearity is obvious and there is no specific rule.

To sum up, the traditional method cannot solve the prediction problem of this time series, and a new method is needed. The general idea is shown in Fig. 3. First, extract the characteristics of each launch waveform, and take the number of launches as the dependent variable to get the feature sequence; second, study the multidimensional feature sequence prediction method to predict the characteristics of the future launch waveform; finally, propose the method to achieve the curve prediction based on the predicted features information.

Although the idea presented in Fig. 3 can accurately predict the EML time series, there are still the following problems to be solved:

1) The general requirements of feature extraction methods. Feature extraction is the key to the prediction of EML time series, which is usually realized manually. A waveform object corresponds to a set of feature extraction methods. When the new sequence objects come, the existing methods cannot be applied directly, so it is necessary to redevelop the feature extraction method, which causes great trouble.
2) Forecast failure demand. It is useless to predict waveforms accurately if it cannot contribute to fault prediction. Therefore, the proposed method must be able to use the predicted waveform and features to predict system fault.

In this article, a new and effective fault prediction method based on waveform and diagnosis knowledge prediction time series will be introduced in the following chapters.

III. Fault Prediction Method of EML System Based on Knowledge Prediction Time Series (FP-BKPTS)

A. Topology of Fault Prediction Algorithm

The topology of the proposed fault prediction algorithm is shown in Fig. 4 and consists of three parts. One is the intelligent feature extraction expert system. In this part, the expert manual feature extraction method for different waveforms is represented as the feature extraction knowledge known by the computer, and an expert system is built to intelligently extract the features of different waveforms to provide feature sets for subsequent prediction. The second is multidimensional feature prediction and waveform prediction. This part includes two stages. The first stage is to build a multidimensional feature set prediction model to accurately predict the future waveform's feature set. The second stage is proposing the algorithm based on the prediction features to restore the prediction waveform. By combining the existing "expert knowledge" of waveform diagnosis, the predicted features and waveform information are applied to diagnose the possible faults in the future, and finally the predicted results are obtained in the last part.

B. Intelligent Feature Extraction Expert System

1) Application Analysis of Feature Extraction Expert System: Every EML system has a large number of pulse waveforms, different waveforms must have different features, so the method of fault prediction by extracting features is not universal. It is found that although there are a large number of pulse waveforms in the EML system, the waveforms produced by different types of EML systems have many common characteristics: for example, the time-domain characteristics are obvious, the waveforms of each launch are similar, and the maximum and minimum value characteristics can reflect the system state to a certain extent. Therefore, the problem of intelligent features extraction can be solved, to a large extent, by building an expert system based on the existing cognitive and feature extraction methods for EML waveforms. Especially, with the enrichment and improvement of feature extraction knowledge base, later feature extraction will become more accurate.

2) Feature Extraction Rule Base: Feature extraction is very important for the accuracy of prediction. Since different curves need to extract different features, generally follow the following principles:

1) The extracted features should be enough to represent the characteristics of waveforms, including time-domain features and frequency-domain features, such as maximum value, frequency, rise time, descent speed, etc.
2) The extracted features must be able to be expressed quantitatively so that they can be converted into time series for prediction.
3) The extracted feature set should be able to fully describe the whole waveform, that is to say, the feature cannot be omitted, so that the whole waveform can be finally recovered without information loss.

Therefore, as shown in Fig. 4, the main rules of the feature extraction rule library are shown in Table I.

3) Feature Extraction:

1) Waveform preprocessing. There is noise and bias error in the collected waveform. If the feature is extracted directly according to the rule of feature extraction, it will cause a non-negligible error, so the waveform should be processed

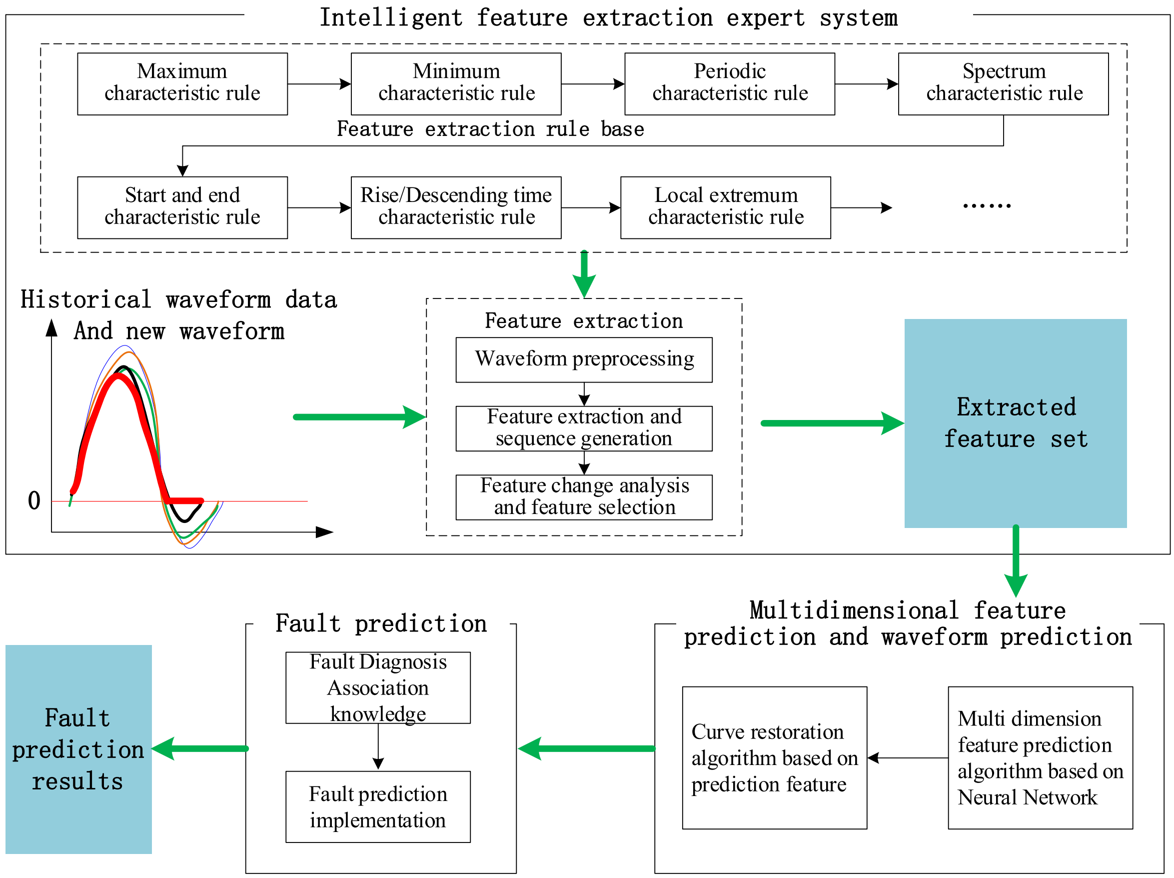

Fig. 4. Work flow of FP-BKPTS algorithm.

TABLE I
FEATURE EXTRACTION RULES

Rule name	Rule definition	Execution method
Max / min rule	The maximum / minimum value of the waveform is feature	Find the max / min value of waveform
Period rule	The period of wave vibration part is feature	Find the vibration part and find its period
Spectrum rule	The frequency that can not be ignored in the frequency domain of waveform is the feature	Fourier transform, and then extract the existing concentrated frequency as the feature
Start/end rule	The initial/end value of a waveform is feature	Extract the initial /end acquisition value of the waveform as feature
Rise / fall time rule	The typical rise / fall time in the waveform is feature	Derivation of waveforms, zero crossing interval as feature
Local extremum rule	The local max / min value in the waveform is feature	Derivative of waveform, taking the point with derivative of 0 as feature

in advance. Waveform preprocessing usually includes median filtering, partial interpolation fitting, resampling, and so on, in order to avoid the error of the subsequent algorithm as much as possible without changing the waveform information.

2) Feature extraction and feature sequence generation. As shown in Table I, detailed feature extraction methods for each feature extraction rule are listed. We extract the characteristics of the waveform collected by each launch, and then take the launch times as the time axis to extend each feature into a feature sequence with the launch times of data points.
3) Feature filtering. Different from the traditional feature extraction based on "expert," the feature expert system will extract a lot of features for each waveform and form a lot of feature sequences. If to predict all sequences, the complexity of the algorithm will be increased, and the accuracy of multidimensional feature sequence prediction will be reduced. Therefore, filtering is necessary. Let the feature sequence of a waveform with n times launches be $t = [T_1, T_2, \ldots, T_n]$, let $\Delta t = [\Delta t_1, \Delta t_2, \Delta t_{n-1}]$, $\Delta t_i = t_{i+1} - t_i$. If the change of Δt point in the difference sequence is very small, or the trend is periodic, then the feature can be eliminated. Because the feature does not change

in numerical value with the increase of launch times, it shows that the feature does not contain the information of system health degradation and can be eliminated.

C. *Multidimensional Features Prediction and Waveform Prediction Algorithm*

1) Multidimensional Feature Sequence Prediction Algorithm:

1) Feature sequences prediction and analysis.

Through the method above, we can get a feature set defined as $[T_1, T_2, \ldots, T_L]$, there are L features. Taking the number of launches as the time axis can form a matrix of characteristic sequences (the number of launches is n), and finally predict the characteristics of the future launch waveform, as shown in formula (1).

$$\begin{bmatrix} T_{11} & T_{12} & \ldots & T_{1n} \\ T_{21} & T_{22} & \ldots & T_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ T_{L1} & T_{L1} & \ldots & T_{L1} \end{bmatrix} -> \begin{bmatrix} T_{1n+1} & T_{1n+2} & \ldots \\ T_{2n+1} & T_{2n+2} & \ldots \\ \ldots & \ldots & \ldots \\ T_{Ln+1} & T_{Ln+2} & \ldots \end{bmatrix}. \quad (1)$$

Equation (2) describes the prediction of the *(n + 1)*th waveform features by the first n launch waveforms data with launch times as the variable

$$\begin{aligned} f(1) &= [T_1(1), T_2(1), \ldots, T_L(1)] \\ f(2) &= [T_1(2), T_2(2), \ldots, T_L(2)] \\ &\ldots\ldots \\ f(n) &= [T_1(n), T_2(n), \ldots, T_L(n)] \\ &\downarrow \\ f(n+1) &= [T_1(n+1), T_2(n+1), \ldots, T_L(n+1)]. \end{aligned} \quad (2)$$

The characteristic quantity of the $(n + 1)$ waveform may be related to the previous multiple launch waveforms. Take the physical principle of the temperature rise of the guide rail as an example to analyze. The temperature source of the guide rail is the heat production of this launch plus the residual temperature of the last launch minus the heat dissipation of this launch, which involves the change of material physical parameters. The internal mechanism is very complex, so it is impossible to build a detailed mathematical model. In summary, it can be qualitatively described that the $(n + 1)$th launch should be related to the curve of the previous p launches.

$$\begin{aligned} T_1(n+1) &= g_1\left(n+1, T_1(n), \ldots, T_1(n-p), T_2(n),\right. \\ &\qquad \left.\ldots, T_2(n-p), \ldots, T_L(n), \ldots, T_L(n-p)\right) \\ &\ldots\ldots \\ T_L(n+1) &= g_L\left(n+1, T_1(n), \ldots, T_1(n-p), T_2(n),\right. \\ &\qquad \left.\ldots, T_2(n-p), \ldots, T_L(n), \ldots, T_L(n-p)\right) \end{aligned} \quad (3)$$

where p is called memory factor, which shows how many times the temperature rise characteristics of previous launches will affect this launch. $g_1, g_2, \ldots, g_L$ are mathematical models of characteristic sequence, each one is usually nonlinear, and the variables include the number of launch times and other coupling characteristics of previous p launches. The prediction problem is transformed into a nonlinear prediction problem with memory information under multivariable coupling.

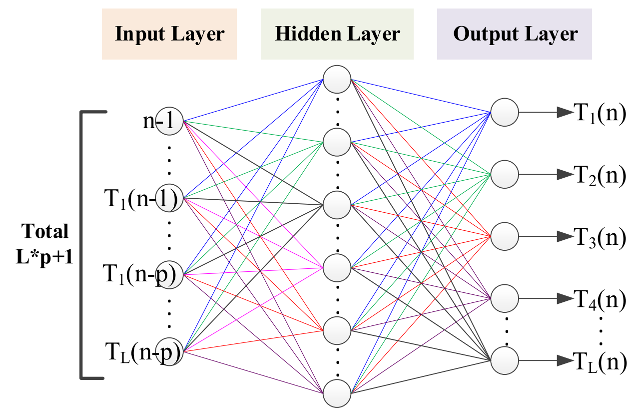

Fig. 5. Multivariable characteristic coupled predictive neural network model.

2) Neural Network Prediction Model.

The above problems are extremely complex. It is almost impossible to deduce the mathematical model of characteristic sequence by theoretical modeling method. Therefore, based on the data itself, it is an inevitable choice to propose a data-driven data modeling method. Because of the nonlinearity of g_1, g_2, …, g_L and the high coupling property of multivariables, using neural network model is a good choice.

Setting the memory factor as p, a two-layer neural network model network is constructed. The output is the characteristic parameters of the predicted next temperature rise curve, and the input is the characteristic parameter set of the temperature rise curve of the previous p launches, such as formula (4)

$$\begin{aligned} &\text{outwork1} = [T_1(n), T_2(n), \ldots, T_l(n)] \\ &= \text{network1}(n-1, T_1(n-1), \ldots, T_1(n-p), T_2(n-1), \\ &\ldots, T_2(n-p), \ldots, T_L(n-p)). \end{aligned} \quad (4)$$

The input of the neural network consists of the first p data points of each feature, with a total of $L * p + 1$ input variables. The output of the model is the predicted value of next launch. The construction of bilevel neural network is shown in Fig. 5.

Before training the neural network, we must first determine the memory factor p and the number of neuron nodes of the hidden layer neural network. The memory factor is determined by the actual memory of the temperature rise of the guide material. It is difficult to determine the value directly, and can only be determined by the program simulation. The number of hidden layer neurons is determined by the complexity of the model. When the prediction model is more complex, the larger the number of hidden layer neurons is, and vice versa. When there is no way to predetermine the complexity of the

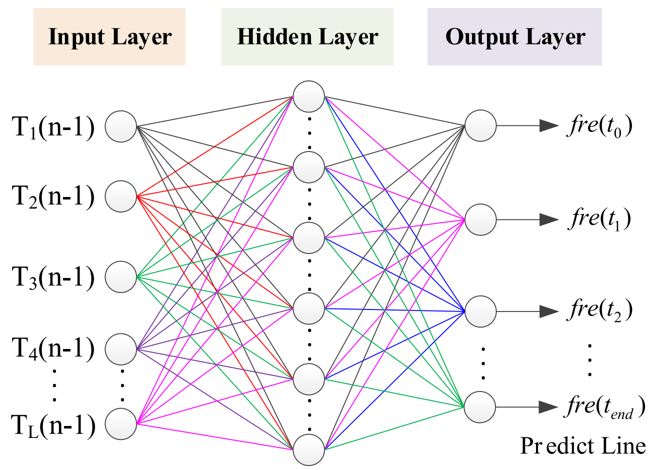

Fig. 6. Curve fitting neural network model.

model, one can consider the size of the data. If there is a large amount of data available for training, one can choose a large number of hidden layers appropriately, and the model will not have insufficient generalization ability. For the small sample data of electromagnetic emission, the number of neurons should not be too large, or the accuracy of the model is not enough. Similarly, the number of neurons should not be lower than the number of input parameters. Otherwise, over-fitting will occur, and the optimal parameters can still be adjusted automatically after attempting.

It should be noted that when the number of launches is less than p, the input data of the neural network model may not exist, which can be replaced by 0.

2) Nonlinear Waveform Restoration Algorithm Based on Predictive Features:

1) Waveform prediction and analysis.

In the previous section, the features extraction and prediction of the waveform collected by a single launch was completed, but only a few feature parameters are obtained by the prediction, and there are many data points of the whole waveform. To fully recover the curve, one must also build a nonlinear data model.

Let the curve characteristic parameters of the nth launch be known, and the curve restoration data model is expressed as formula (5)

$$\text{Pr edict Line} = fre(t, T_1(n), T_2(n), T_3(n), \ldots, T_L(n)). \quad (5)$$

The variables of the data model include time t and all the characteristic parameters. This function is a nonlinear function, and its model will change appropriately with the launching process, and there is no intuitive physical meaning, it cannot be physical modeling, and data-driven method can also be applied.

2) Curve fitting neural network method.

Considering the high nonlinearity of the model, the neural learning network can still be used to acquire the data model. A multiinput multioutput single hidden layer neural network model can be constructed as shown in Fig. 6.

The input is all the characteristic parameters, and the output is the temperature sequence in the sampling time. The sampling rate of temperature series is very high (100 KHz), if set all points of a launch curve as the output of the neural network model, it will need huge computer overhead. The data of 100 Hz resampling is used as the output of the neural network, and the training model is used to restore the temperature curve. The number of hidden layer neurons should not be too large or too small, and the optimal parameters should still be obtained through data testing.

D. Fault Prediction Algorithm Based on Knowledge

After the waveform and its characteristics of next launch are predicted, the fault prediction and analysis can be carried out based on the existing waveform diagnosis knowledge. There are mainly two situations as follows:

1) Fault prediction based on feature threshold. It is found in practice that some characteristics of the waveform (such as the maximum value, period, etc.) will gradually change with the increase of the number of launches, some of them will increase and some of them will decrease. When they exceed a certain threshold value, the system will soon enter a fault state, which can be considered as the fault critical point of the characteristics. When it is predicted that the next value of the feature will exceed the critical point, it can be considered as a fault, so the possibility of the next launch fault is predicted.
2) Fault prediction based on waveform mutation. Sometimes, although all the predicted eigenvalues are in the normal range, each characteristic changes slightly. At this time, there may be a large gap between the predicted whole waveform and the normal waveform (mainly reflected in the waveform shape, which usually needs to be analyzed by "experts"), at this time, the system can also be considered in an abnormal state.

IV. Test and Analysis

The waveforms of temperature rise of rail and recoil stroke measured by the launch test of a prototype electromagnetic railgun are used as the data sources of the proposed algorithm to verify the waveform prediction accuracy and fault prediction ability.

A. Temperature Rise Waveform Prediction and Fault Prediction of Continuous Launch Rail

1) Dataset Description: Taking the rail temperature curve measured in the 15 consecutive dynamic launch test of a certain electromagnetic railgun prototype (as shown in Fig. 1), using a self-developed fiber Bragg grating sensor [19], as the data source into the algorithm operation. The continuous launch interval is set to remain unchanged for 10 s, with a total of 15 consecutive launches, high-frequency data fast sampling rate of 100 KHz (launch instantaneous, continuous 1 s), and slow sampling rate of 10 kHz. Filter and interpolate the original data, and resample

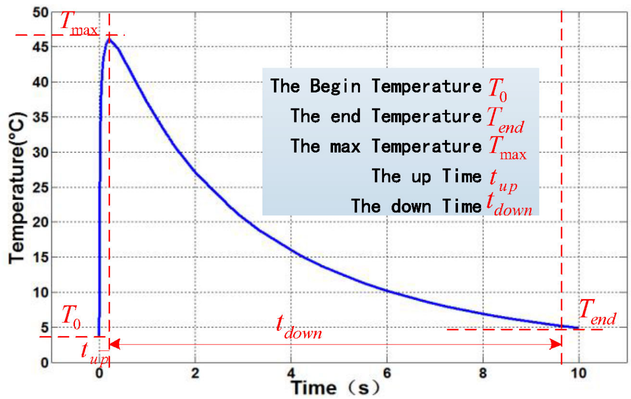

Fig. 7. Schematic diagram of temperature rise waveform feature extraction.

TABLE II
PARAMETERS OF THE NEURAL NETWORK

Memory Factor p	5
Number of Hidden Layer	50
Number of Input Neuron	16
Training Function	Logsig, Purelin
Training Algorithm	Trainrp
Performance Function	Mean Squared Error
Ending Condition	10000 Epoch
Performance Error	0.01

TABLE III
FEATURE PREDICTION RESULTS

Launches	T_0	T_{end}	T_{max}
14	13.138(°C)	12.920(°C)	60.970(°C)
Error (%)	0.94	1.47	0.56
15	13.155(°C)	12.912(°C)	60.988(°C)
Error (%)	0.33	1.81	0.31

according to 1 kHz to get the continuous temperature rise curve as shown in Fig. 2.

2) Features Set Extraction: According to the feature extraction method in Section II-B, five features are extracted, including the starting temperature T_0, the final temperature T_{end}, the maximum temperature $T_{\max}$, the rise time t_{up}, and the fall time t_{down}, as shown in Fig. 7. According to the feature selection rule in Section II-B, the feature t_{up} and t_{down} basically do not change with the increase of the number of launches, so three features that can reflect the health state of the system are retained.

3) Prediction Model and Prediction Results: According to the method proposed in Section II-C, construct the characteristic prediction neural network model. The model parameters are shown in Table II. The data of the previous 13 launches train the neural network model. The characteristic curve between the prediction result and the real value is shown in Fig. 8. Table III shows the predicted characteristic values of the last two launches.

The prediction results show that the prediction model can well predict the multivariable coupling characteristic parameter sequence, and the single step prediction error of the features is less than 1.47%.

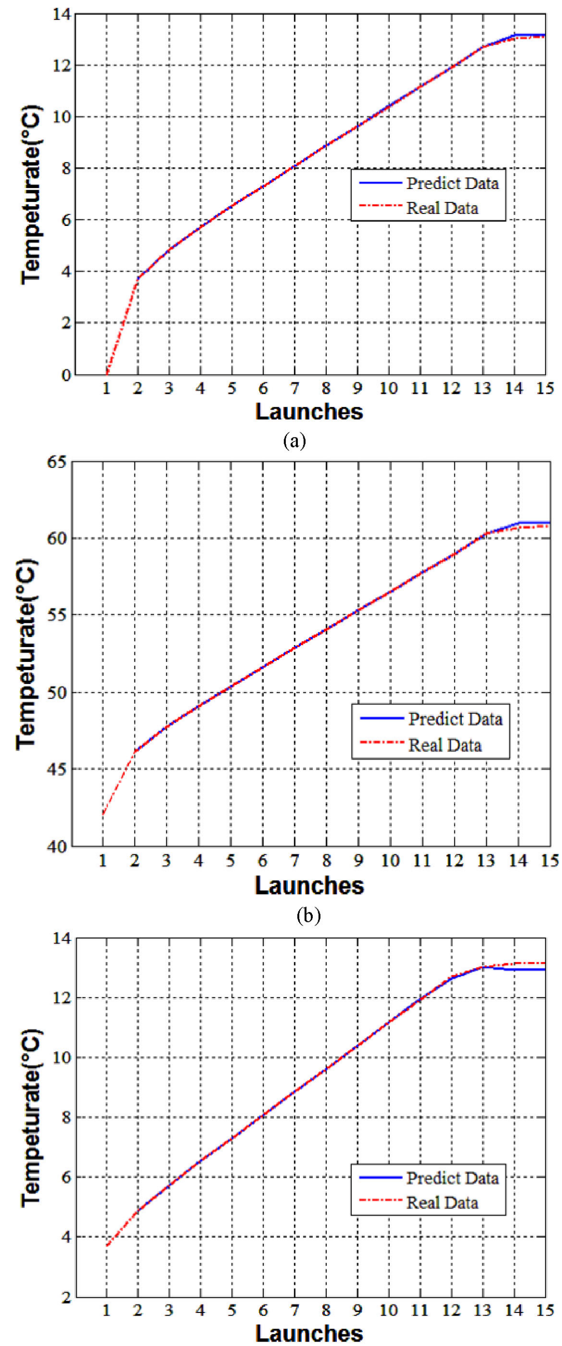

Fig. 8. Prediction results of feature series of temperature rise curves. (a) The beginning moment temperature T_0. (b) The max moment temperature $T_{\max}$. (c)The max moment temperature T_{end}.

According to the proposed method, the curve reduction neural network model is constructed, and the parameter values of the model are shown in Table IV.

The output of the neural network represents that the temperature acquisition time of a launch is divided into 1001 copies. Here, the curve is restored according to the frequency of a data point of 10 ms. Similarly, the data of the previous 13 times are used as training samples to obtain the neural network

TABLE IV
PARAMETERS OF THE NEURAL NETWORK

Number of Hidden Layer	20
Number of Input Neuron	3
Number of Output Neuron	1001
Training Function	Logsig, Purelin
Training Algorithm	Trainrp
Performance Function	Mean Squared Error
Ending Condition	10000 Epoch
Performance Error	0.01

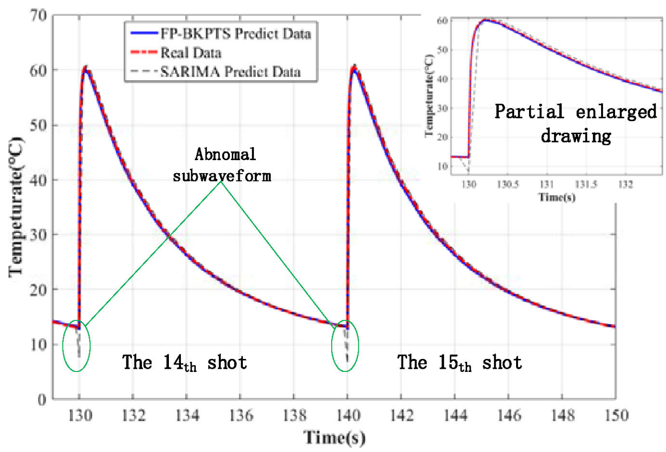

Fig. 9. Comparison results of temperature rise waveform prediction.

TABLE V
FAULT PREDICTION RESULTS OF TEMPERATURE RISE CURVE

Shots	Method/ prediction error	FP-BKPTS	SARIMA
14	T_0 (%)	0.94	----
	T_{end} (%)	1.47	----
	T_{max} (%)	0.56	----
	Mean square error of waveform(K)	0.0216	0.2047
	Fault prediction	No fault	Fault
	Diagnosis analysis	Correct	False alarm
15	T_0 (%)	0.33	----
	T_{end} (%)	1.81	----
	T_{max} (%)	0.31	----
	Mean square error of waveform	0.0294	0.1673
	Fault prediction	No fault	Fault
	Diagnosis analysis	Correct	False alarm

model. In order to quantitatively analyze the effectiveness of the proposed prediction algorithm, SARIMA algorithm, which is most suitable for seasonal time series prediction [17], is used for comparison. The prediction results are shown in Fig. 9, and the quantitative statistics are shown in Table V.

It can be seen from Fig. 9 and Table V that the temperature waveforms predicted by the proposed algorithm for the 14th and 15th launches (thick solid line) are almost consistent with the real values (thick dotted line), with mean square errors of 0.0216 and 0.0294, respectively, while the results of SARIMA

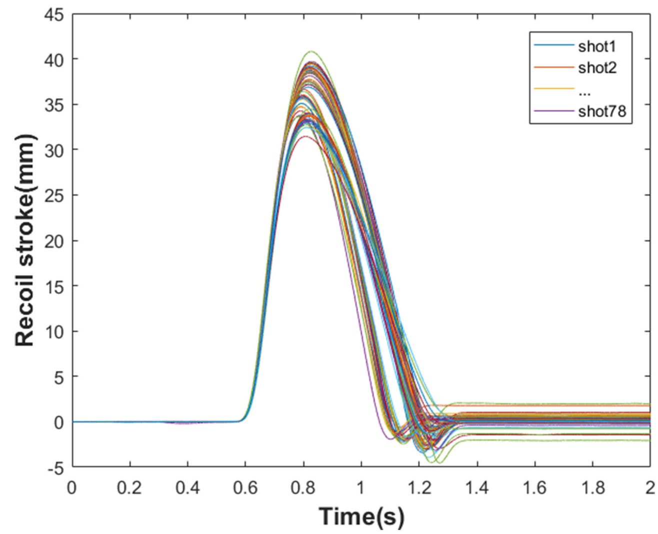

Fig. 10. Recoil travel waveforms of 78 launch tests of electromagnetic railgun.

algorithm (thin dotted line) are much worse, with mean square errors of 0.2047 and 0.1673.

4) Fault Prediction: For the temperature rise curve of the guide rail, two fault diagnosis knowledge have been found in the project:

One is that the peak temperature of the guide rail is less than 120 °C, or the material performance of guide rail will deteriorate. The other is that the shape of the temperature rise waveform measured during normal launch is basically unchanged, but there is a slight difference in the numerical value, and when the abnormal sub waveform appears, it can be judged as a fault.

1) The proposed algorithm fault prediction. Analysis of Fig. 9 shows that the predicted peak temperature characteristics did not exceed the threshold at the 14th and 15th launch. Analysis of Fig. 9 shows that the shape of the predicted temperature rise waveform does not change, and no abnormal subwaveform is found. To sum up, the two launches are predicted to be normal, in line with the actual situation.
2) The SARIMA algorithm fault prediction. It can be seen from Fig. 9 that the abnormal subwaveforms (in the circle) appear in the predicted 14th and 15th launch temperature rise waveforms. Therefore, it is diagnosed that these two launches are fault, and the result is contrary to the fact.

B. Fault Prediction Based on Recoil Stroke Curves

1) Dataset Description: The recoil stroke waveforms measured in 78 launches tests of an electromagnetic railgun prototype, using position transducer made by USA Firstmark Corporation, are used as the proposed algorithm dataset. The waveform dataset is shown in Fig. 10. The sampling rate is 10 kHz, and each launch measurement waveform is 2 s. During the launch test, it was found that with the increase of the number of launches, the rear seat damping of the device increasing continuously, which eventually led to the device's abnormal jamming after the 78th launch. Using the first 74 launches as historical data, the

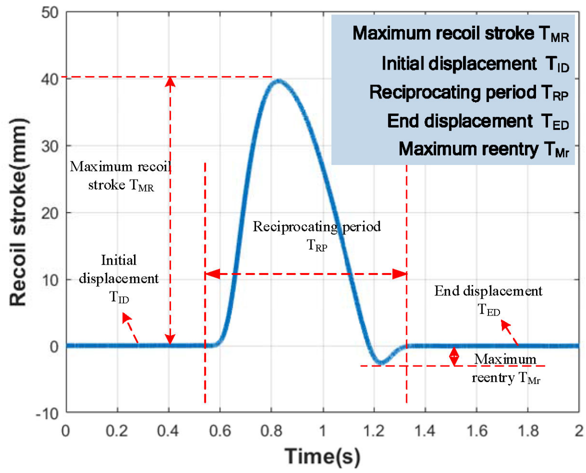

Fig. 11. Schematic diagram for features extraction of recoil travel waveforms.

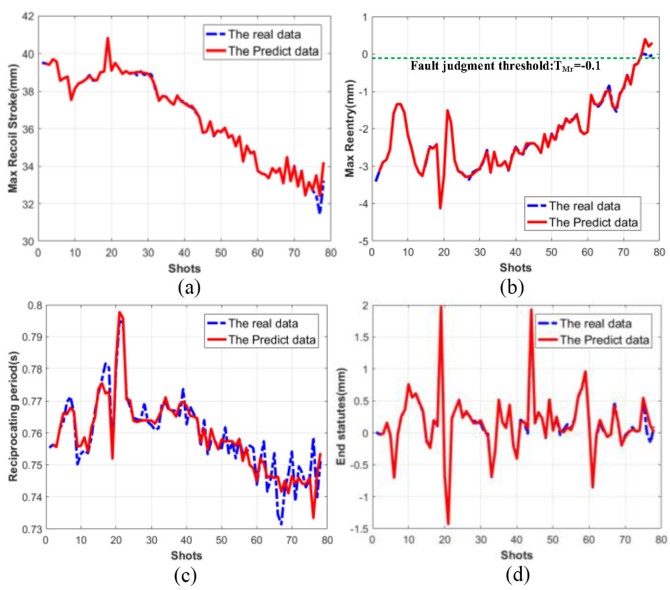

Fig. 12. Prediction results of feature series of recoil stroke curves. (a) The max recoil stroke T_{MR}. (b) The max reentry T_{Mr}. (c) The reciprocating periods T_{RP}. (d) The end displacement T_{ED}.

proposed algorithm is applied to fault prediction to verify the effectiveness of the algorithm.

2) Features Set Extraction: Five features are extracted, such as the maximum recoil stroke T_{MR}, the initial displacement T_{ID}, the reciprocating period T_{RP}, end displacement T_{ED}, and maximum reentry T_{Mr}, as shown in Fig. 11. According to the feature selection rules, the feature T_{ID} do not change with the increase of the number of launches, so four features (T_{MR}, T_{RP}, T_{Mr}, T_{ED}) that can reflect the system health state are retained.

3) Prediction Model and Prediction Results: Construct a neural network model similar to the parameters shown in Table II, and get the feature prediction results as shown in Fig. 12 and Table VI. As shown in Fig. 12, the predicted characteristic curve is close to the actual characteristic curve, and can reflect its change law. In order to quantitatively express the accuracy,

TABLE VI
FAULT PREDICTION RESULTS OF RECOIL STROKE CURVE

Shots	Method/ prediction error	FP-BKPTS	SARIMA
75	T_{MR} (%)	0	----
	$\triangle T_{Mr}/\max(T_{Mr})$ (%)	0.8	----
	T_{RP} (%)	0.02	----
	$\triangle T_{ED}/\max(T_{ED})$ (%)	0.02	----
	Mean square error of waveform(mm)	0.031	0.083
	Fault prediction	Fault	No fault
	Diagnosis analysis	Correct	False dismissal
76	T_{MR} (%)	3.3	----
	$\triangle T_{Mr}/\max(T_{Mr})$ (%)	9.6	----
	T_{RP} (%)	3.3	----
	$\triangle T_{ED}/\max(T_{ED})$ (%)	9.1	----
	Mean square error of waveform(mm)	0.045	0.097
	Fault prediction	Fault	No fault
	Diagnosis analysis	Correct	False dismissal
77	T_{MR} (%)	3.1	----
	$\triangle T_{Mr}/\max(T_{Mr})$ (%)	6.6	----
	T_{RP} (%)	1.0	----
	$\triangle T_{ED}/\max(T_{ED})$ (%)	7.4	----
	Mean square error of waveform(mm)	0.027	0.076
	Fault prediction	Fault	No fault
	Diagnosis analysis	Correct	False dismissal
78	T_{MR} (%)	2.9	----
	$\triangle T_{Mr}/\max(T_{Mr})$ (%)	7.9	----
	T_{RP} (%)	0.3	----
	$\triangle T_{ED}/\max(T_{ED})$ (%)	2.3	----
	Mean square error of waveform(mm)	0.029	0.080
	Fault prediction	Fault	No fault
	Diagnosis analysis	Correct	False dismissal

the prediction error percentages of the characteristic of the four launches are calculated respectively (among them, T_{MR} and T_{ED} are very close to 0, so the historical maximum value can be used as the base number of the percentage, and the prediction accuracy can also be quantitatively expressed). As shown in Table VI, the maximum error of single step prediction of four characteristic quantities is less than 0.8%, and the prediction error of all features under all launches is less than 9.6%, which proves the prediction accuracy of the algorithm.

According to the proposed algorithm, a neural network model based on the feature reduction curve is established, and the first 74 launches data are used as training, and the curve prediction results are shown in Fig. 13. Meanwhile, the comparison prediction results of SARIMA algorithm are set up. It can be seen from the figure that the curve predicted by the proposed algorithm is closer to the real curve than that predicted by SARIMA. The mean square error of prediction is shown in Table VI. The mean square error of the proposed algorithm is 1/2 of SARIMA prediction error, which proves the superiority of the proposed algorithm.

4) Failure Prediction: For the recoil stroke curve of the railgun, the known fault diagnosis knowledge is very little: during

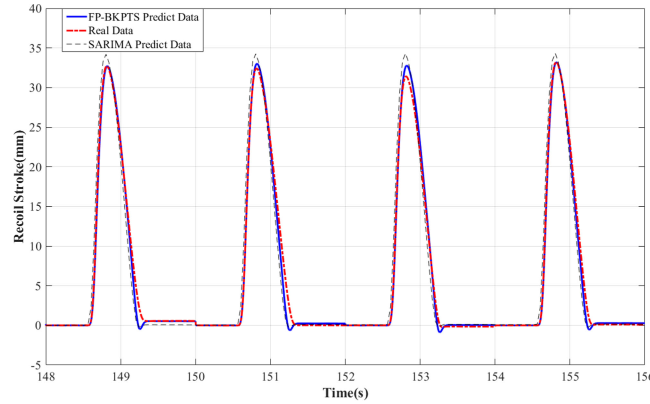

Fig. 13. Comparison results of recoil stroke waveform prediction.

normal launch, the shape of recoil stroke curve changes little and there is no abnormal sub waveform.

1) The SARIMA algorithm fault prediction. The curves predicted of 74th–78th launches by SARIMA has no abrupt change in shape and value, and there is no abnormal wave shape, so it is diagnosed as normal.
2) The proposed algorithm fault prediction. Similarly, there was no anomaly on the predicted curve. However, in the extracted feature prediction, it is found that the feature changes monotonously with the increase of the number of launches, as shown in Fig. 12. Combined with the physical analysis, it is found that $\underline{T}_{\mathrm{Mr}}$ can be used as a feature to describe the degradation of the rear seat friction performance of the launcher, and the critical value of 0 (set as -0.1 for safety) is taken as the fault threshold point. When it reaches 0, it means that the backseat damping changes from under damping to over damping, and the launcher has a great change, which can be regarded as a fault. So all the 74th–78th launches are predicted to be faulty.

In the case of back seat fault prediction in this article, it was not until the 78th launch that the system stopped firing until there was an obvious abnormal noise. At this time, when the device is disassembled, it is found that the connecting mechanism between the barrel and the lens barrel is broken and cannot be repaired. According to the material analysis, the fracture occurred in the 75th launch, and the fracture was aggravated by each launch. In conclusion, the proposed algorithm can accurately predict the fault, but SARIMA has missed the alarm.

V. Conclusion

Aiming at EML system, a fault prediction algorithm based on prediction time series and waveform diagnosis knowledge was proposed. The proposed sequence prediction algorithm solved the problem of feature extraction under different sequences by constructing an expert system, and achieved high precision waveform prediction by extracting features first and then constructing neural network modeling twice. The prediction error of single step feature was less than 1.47%, and the mean square error of curve prediction was 1/2 of the result of SARIMA algorithm. Through the experimental fault prediction of railgun prototype, the proposed algorithm can find fault prediction knowledge at the same time of high-precision prediction, and accurately predict the health status of future launch, without missing alarm and false alarm.

At present, the research is still in its infancy, and further research will be carried out in the direction of improving the feature extraction expert system and multidimensional time series fault prediction.

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