Received February 20, 2019, accepted March 16, 2019, date of publication April 10, 2019, date of current version April 16, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2906895

A Hybrid Method for Life Prediction of Railway Relays Based on Multi-Layer Decomposition and RBFNN

YONGKUI SUN[1], YUAN CAO[2], MINGJUN ZHOU[3], TAO WEN[1], PENG LI[1], AND CLIVE ROBERTS[4]

[1]School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing 100044, China
[2]National Engineering Research Center of Rail Transportation Operation and Control System, Beijing Jiaotong University, Beijing 100044, China
[3]Railway Electrification Transformation Project Construction Headquarters, China Railway Harbin Bureau Group Co., Ltd., Harbin 150001, China
[4]Birmingham Centre for Railway Research and Education, University of Birmingham, Birmingham B15 2TT, U.K.

Corresponding author: Yuan Cao (ycao@bjtu.edu.cn)

This work was supported in part by the Fundamental Research Funds for the Central Universities under Grant 2018YJS021, in part by the National Natural Science Foundation of China under Grant U1734211, Grant U1534208, Grant 61806064, and Grant 61873201, and in part by the National Key Research and Development Program under Grant 2016YFE0200900.

ABSTRACT The railway relay plays an important role in railway systems. Its reliability has a significant effect on the safety of passengers and train operation, which can be reflected using degradation parameters. In this paper, a novel hybrid method based on the multi-layer decomposition and the radial basis function neural network (RBFNN) is proposed for life prediction of railway relays. As the degradation parameter series are usually nonlinear and non-stationary, it is vital to develop an essential method to preprocess the degradation series. In order to improve the prediction accuracy, a multi-layer decomposition method is developed first for data pre-processing, which blends complete ensemble empirical mode decomposition (CEEMD) and an improved variational mode decomposition (IVMD) with a stopping criterion for determining the decomposition modes number. It is noted that IVMD is then used to decompose the high-frequency intrinsic mode functions (IMFs) obtained using CEEMD to improve the prediction accuracy. Furthermore, RBFNN is applied to all the components for prediction. And the prediction results of all the components are reconstructed as the predicted degradation series. Finally, the effectiveness and robustness of the proposed novel hybrid prediction method are verified on one-step prediction and multi-step prediction by comparing other commonly used prediction methods. The experimental results indicate that the proposed hybrid prediction method performs best on the complex degradation parameters of safety relays.

INDEX TERMS Railway relays, life prediction, complete ensemble empirical mode decomposition (CEEMD), improved variational mode decomposition (IVMD), radial basis function neural network (RBFNN).

I. INTRODUCTION

Remaining useful life (RUL) prediction has become an important issue, especially in the field of automatic equipment. As the equipment performance is directly related to the reliability and safety of system operation, it is essential to monitor its operation states [1]–[4]. In railway systems, there are lots of relays used to keep the train control system safe and reliable by transferring command information and status information. At present, the main maintenance means include regular inspection and replacement, which cost lots of manpower. In addition, some relays with good working performance may also be replaced, which leads to low economic benefits. Thus, an accurate life prediction method for railway relays needs to be developed to keep railway systems safer and more effective.

At present, there have been rare studies on railway relay life prediction. However, many scholars have done some research on life prediction for industrial equipment and aerospace relays, which can be used as references. In energy storage systems, a method blending particle filter and support vector regression is proposed to predict the useful life of batteries [5]. In the field of life, a data-driven life prediction method is adopted for LEDs using multidimensional data [6]. In the field of aerospace, a life prediction method based

The associate editor coordinating the review of this manuscript and approving it for publication was Jon Atli Benediktsson.

on auto-regressive and moving average model (ARMA) and wavelet transform model is proposed [7]. In short, RUL prediction is an important step to keep equipment and systems operating reliably. By reviewing previous research, the life prediction methods for relays can be summarized as regression analysis [7], grey system model [8], and neural network [9]. A life prediction method based on ARMA and wavelet transform model has been proposed for aerospace electromagnetic relays with good performance [7]. A. J. Wileman, et al. use grey system model to predict relays' lifetime [8]. These methods can perform well on time series which are smoothed and straightforward, and acquire high prediction accuracies.

However, the nonlinear fitting ability of the above prediction models is not strong. As we know, time series are usually nonlinear, which affect the prediction accuracy of some linear prediction models. In order to address this problem, the back propagation artificial neural networks (BPNN) model has been used in the prediction model, which performs better on nonlinear series [10]. However, traditional single prediction methods can hardly reveal the nonlinearity and non-stationarity properties of time series. Taking that into consideration, some life prediction methods combing prediction model and decomposition technology were proposed. A hybrid prediction model based on wavelet packet decomposition, phase space reconstruction and Volterra series was proposed [11]. And Li proposed a prediction model combining ensemble empirical mode decomposition (EEMD), phase space reconstruction and RBFNN [12]. The decomposition technology can improve the prediction accuracy to a certain degree.

But there are still some defects which need to be solved. For example, the prediction results of the high-frequency components are usually not satisfying, which will have an influence on the prediction accuracy. The prediction performances need to be further improved since the single decomposition method also cannot reveal all the nonlinearity and non-stationarity properties of time series. Note that the decomposition technique can improve the prediction accuracy, it provides the possibility to further improve the prediction accuracy using multi-layer decomposition method, which is the motivation of this paper. In addition, it is noted that the most recent studies are based on the one-step prediction methods. However, multi-step prediction with high accuracy is necessary in many scenarios to prevent potential dangers happening by taking some measures in advance.

Meantime, it is noted that the empirical mode decomposition (EMD), proposed by Huang *et al.*, is a preferable data-driven method, especially suitable for nonlinear and non-stationary data [13]. Thus, it provides the application possibility for life prediction of railway relays. In recent years, EMD has been widely used in data processing [14], [15]. However, EMD has some defects, such as mode mixing and endpoint effect. Thus, many improved EMD methods have been proposed, such as the EEMD method [16] and complete ensemble empirical mode decomposition (CEEMD) method [17]. EMD and its improved versions have been widely used in fault diagnosis [18] and feature extraction [19]. At present, there have been some tries [12] for life prediction using EEMD. But there are still some flaws. First, the constructed signal contains residual noise which may affect the prediction accuracy. Besides, the prediction accuracy is not high for one-step prediction. Especially, the CEEMD takes the concept of eliminating reconstruction noise into consideration, which is the basis of high prediction accuracy. In 2014, K. Dragomiretskiy proposed a novel and non-recursive decomposition method called VMD, which is constructed on basis of mathematical derivation [20]. It can ensure decomposition optimality in the sense of minimum sum of modes' bandwidths. VMD has been used in many fields [21], [22]. As a novel technology, it also has some defects. For example, the decomposition modes number needs to be determined in advance, while there are no uniform standards.

Taking the above theoretical background into account, a novel prediction model (CEEMD-IVMD-RBFNN) based on multi-layer decomposition technology and RBFNN is proposed. First, the CEEMD method is utilized for preprocessing on nonlinear time series of the railway relay's degradation parameter. In order to obtain higher prediction accuracy, a multi-layer decomposition method is proposed. After IMFs being obtained by using CEEMD, an improved VMD (IVMD) is applied to the high-frequency IMFs to do the secondary decomposition. To improve the prediction accuracy, a stopping criterion for VMD is proposed to reduce the error of reconstructed signals. The neural network has strong learning abilities, which is proper to be used as the prediction model. The performance of BPANN model is closely related to data quantity and quality, and the selection of model parameters. In comparison, the training speed of RBFNN is faster than BPNN, and RBFNN usually can avoid the local optimal solutions [23]. So, RBFNN is adopted as the prediction model in this paper. All the predicted sub-series are reconstructed as the predicted series of the original series. The experimental results and comparison demonstrate the proposed CEEMD-IVMD-RBFNN model performs best in railway relay's life prediction.

The remainder of this paper is summarized as follows. Section II introduces CEEMD, an improved VMD, and RBFNN model. Then, a hybrid model based on CEEMD, IVMD, and RBFNN is proposed. In Section III, simulation results and discussion are given. At last, conclusion and future works are summarized in Section IV.

II. THE PROPOSED CEEMD-IVMD-RBFNN MODEL

In this part, a hybrid model based on CEEMD, IVMD, and RBFNN is proposed. And the structure of this model is given as Fig. 1. First, CEEMD is applied to the time series of railway relays. A series IMFs ($imf_1 \sim imf_n$) and a residue can thus be obtained. Then, IVMD is used to do the secondary decomposition for the first m high-frequency IMFs where $Modes_1, Modes_2, \cdots, Modes_m$ denote the decompo-

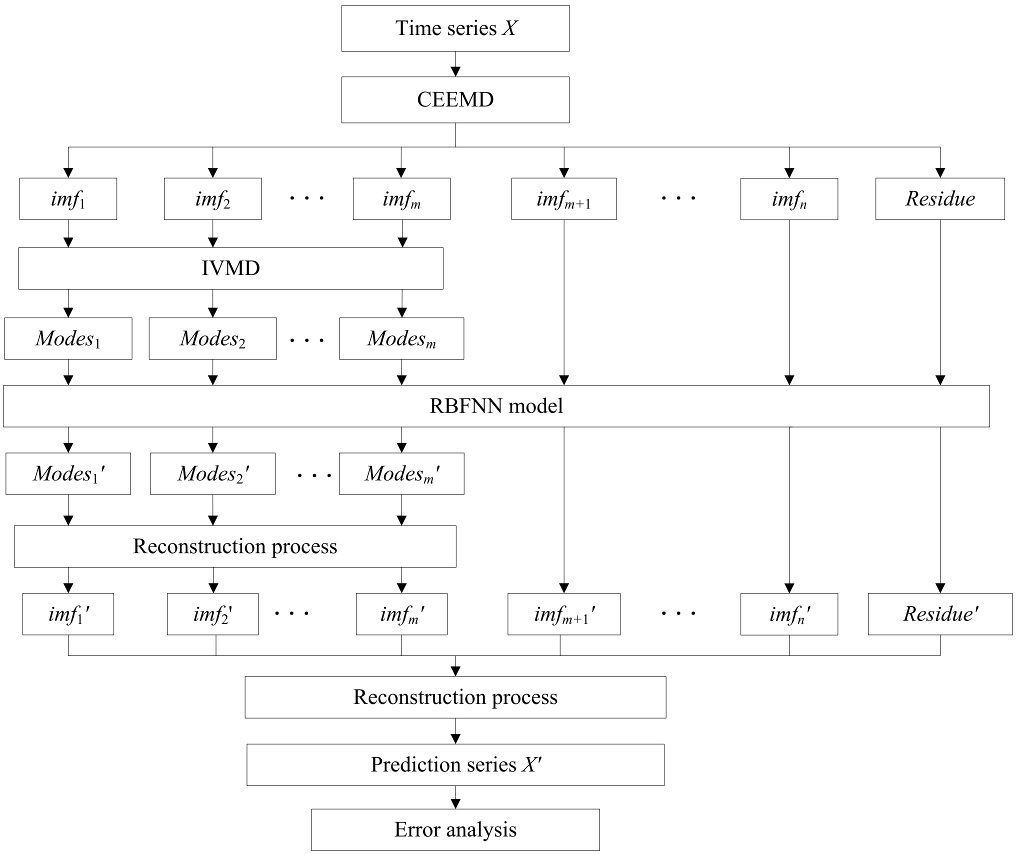


FIGURE 1. **The structure of the CEEMD-IVMD-RBFNN model.**

sition results of $imf_1, imf_2, \cdots, imf_m$, respectively. Further, the RBFNN model is used as the prediction model. The final prediction series can be obtained using two reconstruction processes. The selection of m and the superiority of the proposed multi-layer decomposition prediction model are detailedly described in Section III.

A. THE CEEMD METHOD

As a data processing method for nonlinear and non-stationary signal, EMD has been successfully applied to practical engineering. Finally, the original signal can be decomposed into several IMFs and a residue. Every IMF should satisfy the following two conditions: (1) the numbers of extreme points and zero-crossing points are equal or differ only by one; (2) the mean of upper and lower envelopes is zero at any point [24]. Aiming to deal with mode mixing of EMD, Wu and Huang proposed a noise-assisted method named EEMD [16]. But the reconstructed signal still includes residual noise. CEEMD has been proposed to solve the problems of EMD and EEMD, which can reconstruct the signal completely [17]. Meanwhile, it needs fewer iterations which reduces the computational cost. Compared to EEMD, the method adds noise in each decomposition stage. The procedures of CEEMD are as follows.

1. The original signal $x(t)$ is mixed with a fixed percentage of zero-mean and unit-variance Gaussian white noise. Then, EMD is used to obtain the first intrinsic mode function of the signal with noise. After n times of decompositions using the signal with different Gaussian noise, the first IMF can be obtained using

$$imf_1 = \frac{1}{n}\sum E_1(x(t) + \varepsilon_0 w_i(t)) \tag{1}$$

where imf_1 is the first decomposition component of the target signal, ε_0 is a fixed coefficient, w_i is Gaussian white noise, and E_1 represents an operator to obtain the first IMF using EMD method. The procedures of EMD can be seen in [13].

2. Calculate the first residue using

$$r_1 = x(t) - imf_1 \tag{2}$$

3. Add Gaussian white noise to r_1 and make n times of decompositions using EMD. Then, the second IMF can be defined as

$$imf_2 = \frac{1}{n}\sum_{i=1}^{n} E_1(r_1 + \varepsilon_1 E_1(w_i(t))) \tag{3}$$

4. For $j = 2, \cdots, L$, calculate the j-th residue.

$$r_j = r_{j-1} - imf_j \tag{4}$$

5. Add Gaussian white noise to r_l and make n times of decompositions using EMD. And the $(j+1)$-th IMF can be

obtained as

$$imf_{j+1} = \frac{1}{n}\sum E_1(r_j + \varepsilon_j E_j(w_i(t))) \tag{5}$$

where E_j is an operator to obtain the j-th IMF.

6. Return to Step 4. If r_l is monotonous or only has one extreme point, the decomposition algorithm ends. And $r = r_l$ is the residue. Finally, the original signal can be decomposed as

$$x(t) = \sum_{i=1}^{L} imf_i + r \tag{6}$$

If r_k doesn't satisfy the above conditions, return to Step 5.

B. THE IVMD

1) THE VMD ALGORITHM

As a new non-recursive signal processing method, VMD can decompose a time series into a group of band-limited modes (u_k). The essence of the VMD algorithm is to construct the variational problem and seek its optimal solution to determine the bandwidth and center frequency of each mode by minimizing the sum of the bandwidths of all the decomposed modes. In order to determine the bandwidth of each mode, the following procedures are utilized [25]. a) the mode u_k is processed by the Hilbert transform to obtain its unilateral spectrum; b) add the estimated center frequency e^{-jwkt} to modulate the spectrum of each mode u_k onto the baseband; c) determine the bandwidth of each mode by calculating the L^2-norm of the gradient of the demodulated Signal. Assuming K modes are obtained by applying VMD to the original signal, and the variational constraint problem can be expressed as:

$$\begin{aligned} &\min_{\{u_k\},\{w_k\}} \{\sum_{k=1}^{K} \|\partial_t[(\delta(t) + \frac{j}{\pi t}) * u_k(t)]e^{-jw_k t}\|_2^2\} \\ &s.t. \sum_{k=1}^{K} u_k = f \end{aligned} \tag{7}$$

where $\{u_k\} = \{u_1, u_2, \cdots, u_K\}$ is the K sets of modes, $\{w_k\} = \{w_1, w_2, \cdots, w_K\}$ is the corresponding center frequencies, and f is the original signal.

In order to solve the above variational constraint problem, the quadratic penalty factor α and Lagrange multipliers λ are introduced into the model. Then, the above constraint problem can be converted to an unconstraint one, as

$$\begin{aligned} &L(\{u_k\}, \{w_k\}, \lambda) \\ &\quad = \alpha\|\partial_t[(\delta(t) + \frac{j}{\pi t}) * u_k(t)]e^{-jw_k t}\|_2^2 \\ &\qquad + \|f(t) - \sum_{k=1}^{K} u_k(t)\|_2^2 + \langle\lambda(t), f(t) - \sum_{k=1}^{K} u_k(t)\rangle \end{aligned} \tag{8}$$

Then, a sequence of iterative sub-optimizations called alternate direction method of multipliers (ADMM) [26] is used to seek the saddle point of augmented Lagrange multipliers. Finally, the solutions of modes u_k and center frequency w_k can be expressed as

$$\begin{aligned} \hat{u}_k^{n+1}(w) &= \frac{\hat{f}(w) - \sum_{i\neq k} \hat{u}_i(w) + \frac{\hat{\lambda}(w)}{2}}{1 + 2\alpha(w - w_k)^2} \\ w_k^{n+1} &= \frac{\int_0^\infty w|\hat{u}_k(w)|^2 dw}{\int_0^\infty |\hat{u}_k(w)|^2 dw} \end{aligned} \tag{9}$$

where $\hat{f}(w)$, $\hat{u}_i(w)$, $\hat{\lambda}(w)$ and $\hat{u}_k^{n+1}$ represent the Fourier transforms of $f(t)$, $u_i(t)$, $\lambda(t)$ and $u_k^{n+1}(t)$, respectively.

2) IVMD USING A STOPPING CRITERION

It is noted that the number K of modes should be set before the decomposition process. Too small K will lead to severe distortion, which will have an influence on the prediction accuracy. Whereas too large K will lead to unnecessary decomposition, which may make the decomposition process more time-consuming. In this paper, an improved VMD combining VMD and a stopping criterion for determining K is proposed. The procedures are as follows:

1. Set the maximum of K as K_{max}.
2. Set $K = 2$, and apply VMD to the signal.
3. Calculate the correlation coefficient cor between the reconstructed signal and the original signal. The algorithm ends when K reaches K_{max} or the correlation coefficient cor is larger than the threshold.

C. RBFNN

RBFNN have been widely used because of its simple structure and the strong ability to approximate any nonlinear function. The RBF neural network consists of three layers: input layer, hidden layer and output layer. The transformation from the input space to the hidden layer space is nonlinear. And the transformation from the input to the j-th hidden neuron can be expressed as

$$h_j(X) = \exp(-\frac{\|X - c_j\|^2}{2\sigma^2}) \tag{10}$$

where c_j and σ denote the clustering center and a kernel width parameter of the j-th hidden neuron, respectively.

While the spatial transformation from the hidden layer space to the output layer is linear. The output y_m can be obtained by

$$y_m = \sum_{j=1}^{n} w_j h_j(X) \tag{11}$$

where w_j is the weight from the j-th hidden neuron to the output, and n denotes the number of hidden neurons.

III. RESULTS AND DISCUSSION

The investigated railway relay model is 3RT1034-3XF40-0LA2. And the parameters including contact resistance, closing time, bounce time and release time are collected by relay life detection system (see Fig. 2). There are totally 986 release

FIGURE 2. **The device for data collection.**

time series points to be analyzed. These points are collected every 100 actions of the railway relay.

Analyzing on the degradation parameters of the railway relays using the analysis method we have proposed [9], we find that as for this type of relays, the release time is the most effective parameter which can reflect the degradation regulation. Thus the release time is selected as the research object in this paper. In order to deal with the nonlinear and non-stationary release time series, the CEEMD method is used to do pre-processing. The decomposition results of release time series is shown in Fig. 3.

From Fig. 3, we can see that the release time series is decomposed into 8 IMFs and a residue. The first several IMFs contain lots of high-frequency information comparing with the rest IMFs. While the residue reflects the changing trend of release time series. In order to predict the release time series, the RBFNN model is trained using the first 800 values, while the rest 186 values are used as test set. Here, the idea of phase space reconstruction (PSR) [24] is adopted by selecting embedding dimension and time lag as 5 and 1, respectively. That means we use the former 5 series points (training point) to predict the next value (output point). The RBFNN model is trained using the phase space series (set of training points) and corresponding output series (set of output points). The number of neurons equals that of input points, and the spread parameter of radial basis functions is determined as 1000 by many simulations. Then, the prediction results of the remaining 186 values are obtained as Fig. 4 using the one-step prediction.

It can be seen from Fig. 4 that the prediction results of the first 3 IMFs cannot fit the real values very well, which will cause the reconstructed release time prediction series inaccurate. Comparatively, as for the other lower-frequency IMFs and the residue, the RBFNN performs better with higher accuracies. So, the first 3 IMFs are further studied to

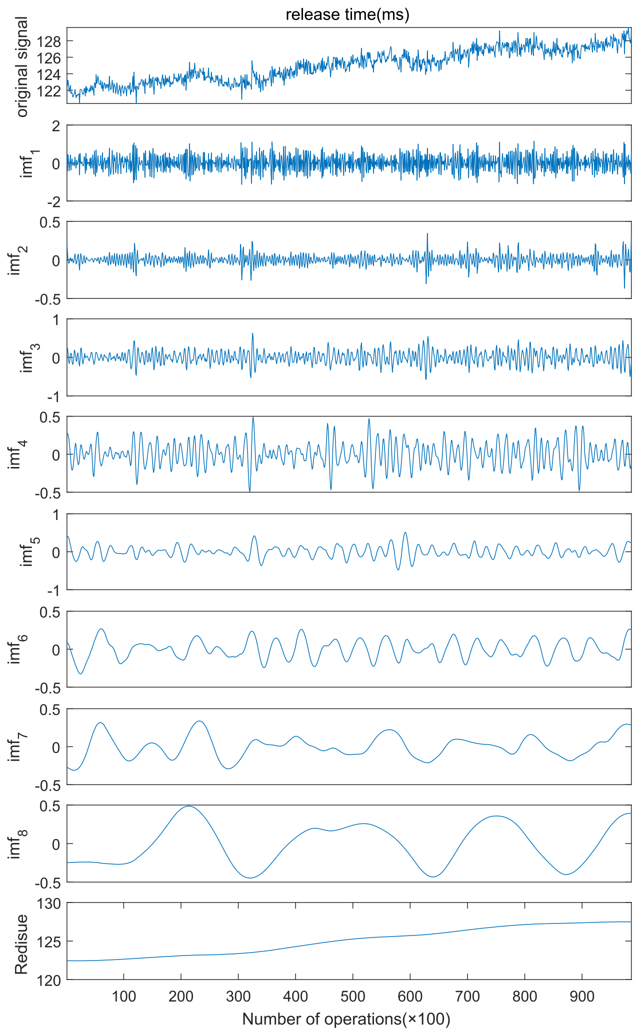


FIGURE 3. **The decomposition results of release time based on CEEMD.**

improve the prediction accuracy. Here, the IVMD mentioned in Section II is used to do further decomposition for $imf_1 \sim imf_3$. In this paper, K_{max} is set as 15, and correlation coefficient threshold cor is set as 0.995 to ensure the prediction accuracy. By applying the improved VMD, the first 3 IMFs can be decomposed into 14 modes, 13 modes, and 10 modes, respectively. Then, the RBFNN model is applied to these modes for one-step prediction. The reconstruction process by calculating the sum of the predicted modes is carried out to obtain the prediction results of $imf_1 \sim imf_3$. The prediction results using IVMD and RBFNN (IVMD-RBFNN) are given as Fig. 5.

Fig. 5 indicates that the one-step prediction accuracy of $imf_1 \sim imf_3$ using IVMD-RBFNN has been obviously improved compared with Fig. 4, which demonstrates the possibility to improve the prediction accuracy using multi-layer decomposition technology combining CEEMD and IVMD. Then, the proposed novel hybrid prediction method named CEEMD-IVMD-RBFNN with multi-layer decomposition technology is compared against the existing

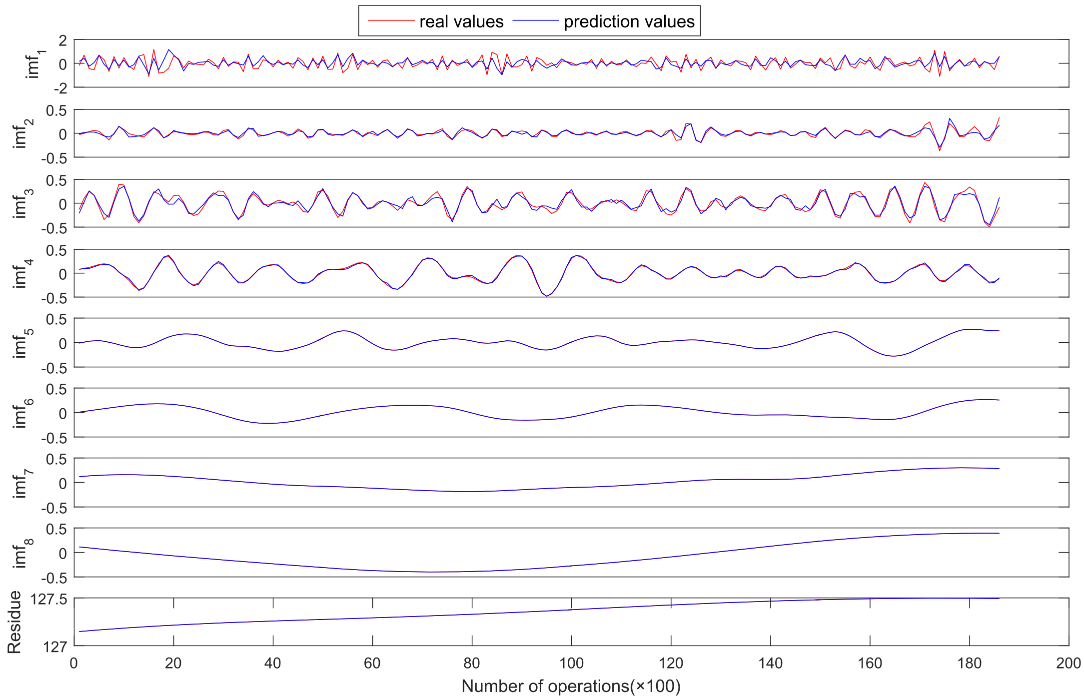


FIGURE 4. **The one-step prediction results using CEEMD-RBFNN.**

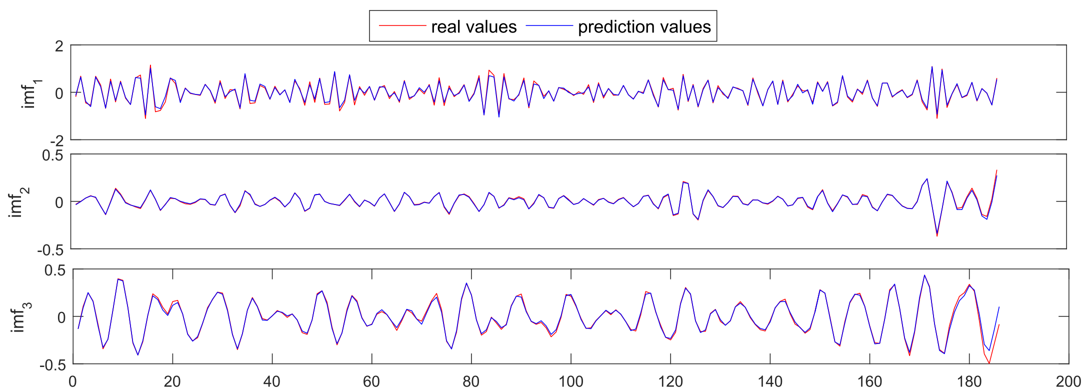


FIGURE 5. **The prediction results of $imf_1 \sim imf_3$ using IVMD-RBFNN.**

RBFNN model, the hybrid model combining CEEMD and RBFNN (CEEMD-RBFNN), and the hybrid model combining IVMD and RBFNN (IVMD-RBFNN). The one-step prediction results are shown in Fig. 6.

It is seen that RBFNN performs worst due to the strong nonlinearity and non-stationarity properties of the release time series. Applying the decomposition techniques (CEEMD and IVMD) can improve the prediction accuracy to a certain degree. While the proposed CEEMD-IVMD-RBFNN can further improve the prediction accuracy. To quantitatively evaluate the prediction performance of the proposed method, the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean square error (RMSE) are adopted. The calculation formulas of MAE, MAPE, and RMSE are given as follows.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x_i'| \tag{12}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{x_i - x_i'}{x_i}| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_i')^2} \tag{14}$$

where x_i is the real value, x_i' is the prediction value, and n denotes the length of the time series.

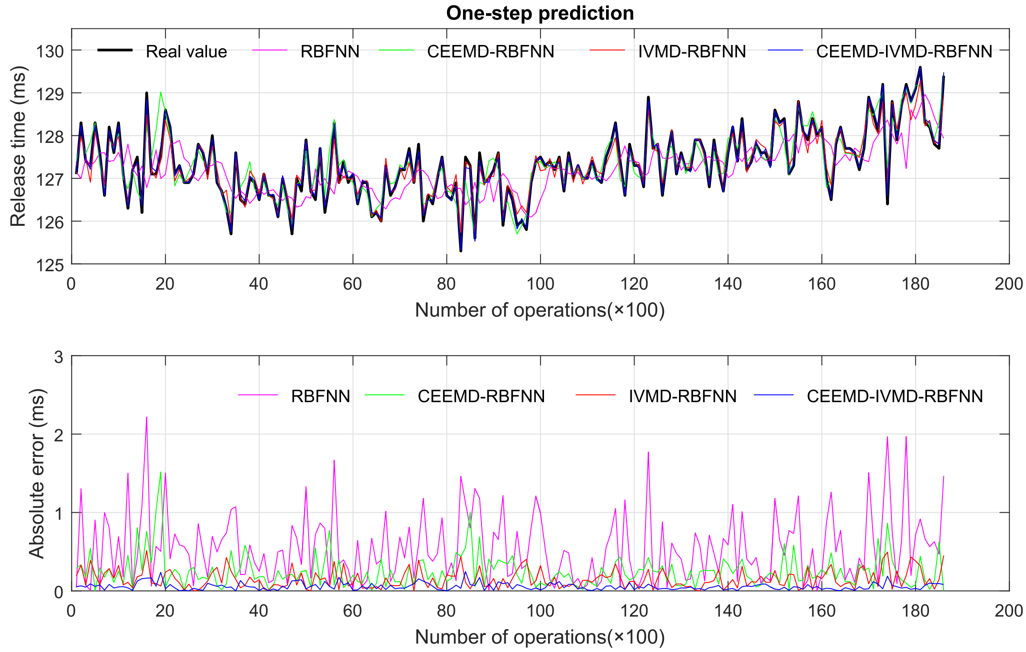


FIGURE 6. One-step prediction results using RBFNN, CEEMD-RBFNN, IVMD-RBFNN, and CEEMD-IVMD-RBFNN.

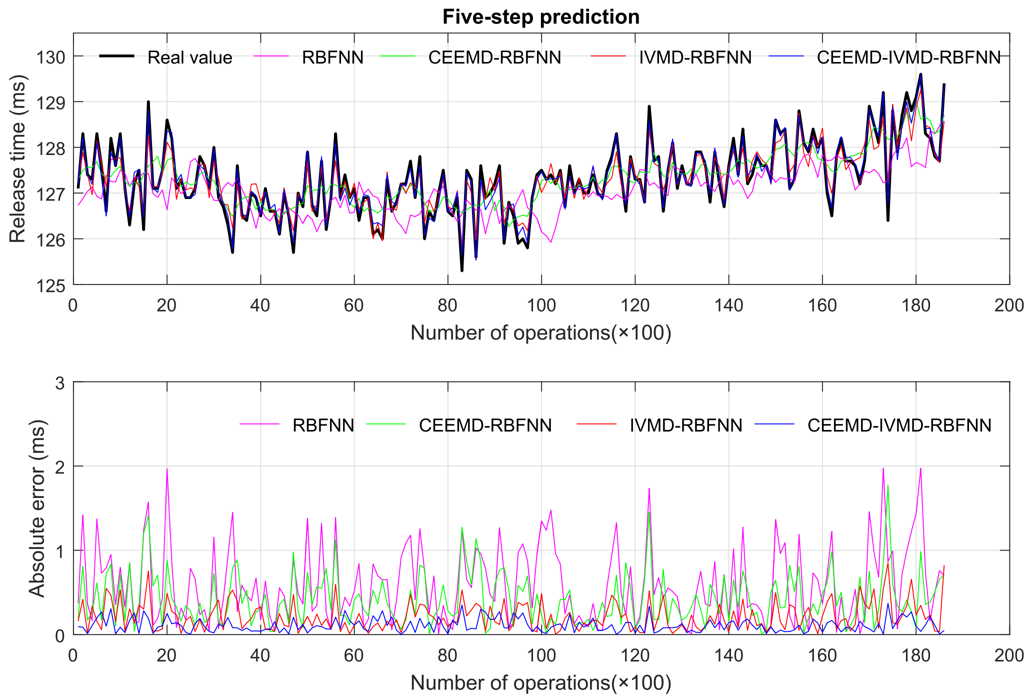


FIGURE 7. Five-step prediction results using RBFNN, CEEMD-RBFNN, IVMD-RBFNN, and CEEMD-IVMD-RBFNN.

Note that multi-step prediction is an essential step to pre-maintenance. Pre-maintenance for railway relays is of great significance to foresee the potential failures in advance in order that proper measures, such as replacement, can be taken to keep railway signaling systems safe. In this paper, two-step, three-step, four-step, and five-step are selected. Especially, the five-step prediction results are given in Fig. 7.

By using Eqs. (12), (13) and (14), the indexes (MAE, MAPE, and RMSE) are calculated and shown in Table 1 and Fig. 8. It can be concluded that in the same step prediction, RBFNN model has the lowest prediction accuracy. The application of CEEMD and IVMD can improve the prediction accuracy. And the IVMD-RBFNN model performs better than the CEEMD-RBFNN model. While the

TABLE 1. The Evaluation Indexes of RBFNN, CEEMD-RBFNN, IVMD-RBFNN, and CEEMD-IVMD-RBFNN.

	Indexes	Models			
		RBFNN	CEEMD-RBFNN	IVMD-RBFNN	CEEMD-IVMD-RBFNN
One-step	MAE	0.5529	0.246	0.1496	0.0554
	$MAPE$	0.0043	0.0019	0.0012	0.0004
	$RMSE$	0.7082	0.3235	0.1905	0.0709
Two-step	MAE	0.5814	0.3835	0.1468	0.0635
	$MAPE$	0.0046	0.003	0.0012	0.0005
	$RMSE$	0.725	0.4724	0.1887	0.0805
Three-step	MAE	0.5963	0.3895	0.1534	0.0827
	$MAPE$	0.0047	0.0031	0.0012	0.0006
	$RMSE$	0.7429	0.4827	0.197	0.1036
Four-step	MAE	0.6154	0.409	0.1784	0.0986
	$MAPE$	0.0048	0.0032	0.0014	0.0008
	$RMSE$	0.778	0.5058	0.2302	0.1244
Five-step	MAE	0.5996	0.4223	0.2141	0.1093
	$MAPE$	0.0047	0.0033	0.0017	0.0009
	$RMSE$	0.7512	0.5254	0.2745	0.1357

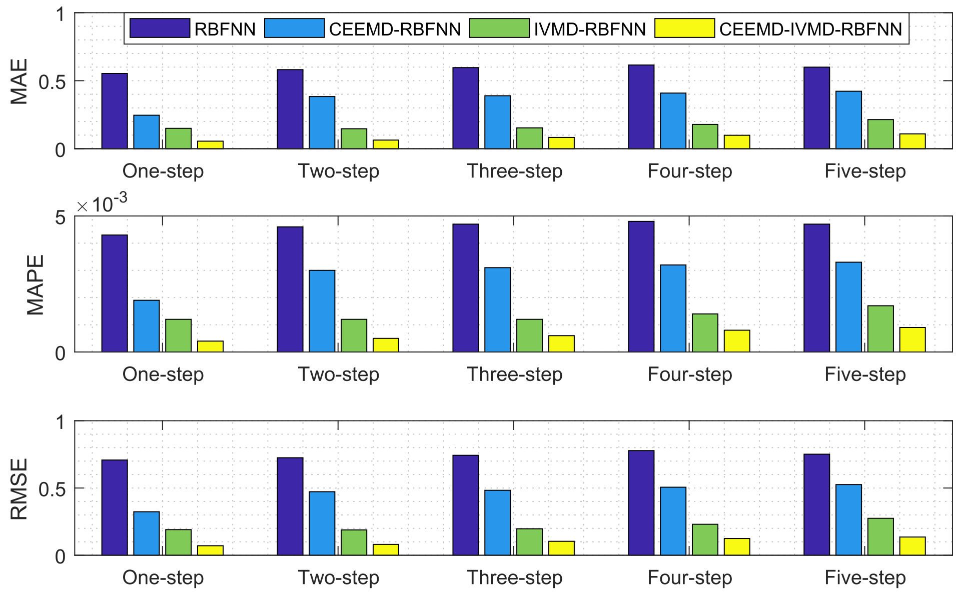


FIGURE 8. Performance comparison of different methods.

proposed CEEMD-IVMD-RBFNN model combining multi-layer decomposition and RBFNN has better performance than the other two models which only utilize single decomposition technology. In addition, as the prediction step increases, the prediction performance of all models decreases because of cumulative errors. The MAE, MAPE, and RMSE of the CEEMD-IVMD-RBFNN model are always smaller than the other models. Besides, the five-step prediction results of the proposed hybrid model is even smaller than the one-step one of the IVMD-RBFNN model, which indicates its superiority and robustness for one-step prediction and multi-step prediction.

IV. CONCLUSION

The most commonly used prediction models for relays are based on regression models, grey system model, and neural network. However, such single prediction models perform unsatisfactorily on nonlinear and non-stationary time series. Hybrid prediction models combining prediction model and single decomposition technology cannot reflect all the nonlinearity and non-stationarity properties of the complex time series. In this paper, by improving VMD algorithm, a multi-layer decomposition technology combining CEEMD and IVMD is proposed. Then, RBFNN is applied for prediction. The proposed CEEMD-IVMD-RBFNN model can solve the defects of poor nonlinear prediction ability of models with single prediction methods on the high-frequency components. It can further improve the prediction accuracy of prediction methods combing single decomposition technology, especially for multi-step prediction. Experimental studies indicate that the proposed CEEMD-IVMD-RBFNN model performs best for both one-step prediction and multi-step prediction on the degradation time series with high nonlinearity and non-stationarity. Especially, it still ensures the highest prediction accuracy and robustness in case of multi-step prediction, which is important for pre-maintenance.

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

1. An improved VMD is proposed by determining the number of decomposition modes using correlation coefficient between the reconstructed signal and the original signal, which can ensure decomposed modes include almost all the information of the original signal.

2. A multi-layer decomposition method based on CEEMD and IVMD is proposed. Then, the hybrid model based on the multi-layer decomposition method and RBFNN is established, named CEEMD-IVMD-RBFNN. It is adopted to predict the release time of railway relays with a higher accuracy compared to the prediction models using single decomposition technology.

3. Besides the one-step prediction, the proposed method also performs well on multi-step prediction, which is of great importance for the railway relay pre-maintenance.

In the future, it is suggested that more parameters of railway relays are to be studied especially on their degradation mechanism. Besides, a multi-parameter prediction model needs to be explored to further improve the prediction accuracy.

REFERENCES

[1] Y. Cao, Y. Zhang, T. Wen, and P. Li, "Research on dynamic nonlinear input prediction of fault diagnosis based on fractional differential operator equation in high-speed train control system," *Chaos*, vol. 29, no. 1, 2019, Art. no. 013130. doi: 10.1063/1.5085397.

[2] Y. Cao, L. Ma, S. Xiao, X. Zhang, and W. Xu, "Standard analysis for transfer delay in CTCS-3," *Chin. J. Electron.*, vol. 26, no. 5, pp. 1057–1063, 2017.

[3] F. Ding, L. Xu, F. E. Alsaadi, and T. Hayat, "Iterative parameter identification for pseudo-linear systems with ARMA noise using the filtering technique," *IET Control Theory Appl.*, vol. 12, no. 7, pp. 892–899, May 2018.

[4] Y. Cao, P. Li, and Y. Zhang, "Parallel processing algorithm for railway signal fault diagnosis data based on cloud computing," *Future Gener. Comput. Syst.*, vol. 88, pp. 279–283, Nov. 2018.

[5] J. Wei, G. Dong, and Z. Chen, "Remaining useful life prediction and state of health diagnosis for lithium-ion batteries using particle filter and support vector regression," *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5634–5643, Jul. 2018.

[6] K. Lu, W. Zhang, and S. Bo, "Multidimensional data-driven life prediction method for white LEDs based on BP-NN and improved-Adaboost algorithm," *IEEE Access*, vol. 5, pp. 21660–21668, 2017.

[7] Z. Wang, S. Shang, G. Zhai, and W. Ren, "Research on storage degradation testing and life prediction based on ARMA and wavelet transform model for aerospace electromagnetic relay," in *Proc. IEEE 60th Holm Conf. Elect. Contacts*, Oct. 2014, pp. 1–8.

[8] A. J. Wileman and S. Perinpanayagam, "Integrated vehicle health management: An approach to dealing with lifetime prediction considerations on relays," *Microelectron. Rel.*, vol. 55, nos. 9–10, pp. 2165–2171, 2015.

[9] Y. Sun, Y. Cao, Y. Zhang, and C. Xu, "A novel life prediction method for railway safety relays using degradation parameters," *IEEE Intell. Transp. Syst. Mag.*, vol. 10, no. 3, pp. 48–56, Mar. 2018.

[10] Z. Wang, S. Fu, S. Shang, and W. Chen, "New forecasting method of closing time for aerospace relay in storage accelerated degradation testing," in *Proc. 11th Int. Conf. Rel., Maintainability Safety*, Oct. 2016, pp. 1–5.

[11] L. Li, Y. Han, W. Chen, and D. Sun, "An improved wavelet packet-chaos model for life prediction of space relays based on volterra series," *PLoS ONE*, vol. 11, no. 6, 2016, Art. no. e0158435.

[12] W. Li, N. Wang, D. Shao, and Z. Li, "RBF network model with EEMD phase space reconstruction application in storage life prediction of sealed electromagnetic relay," *Elect. Energy Manage. Technol.*, vol. 2015, no. 8, pp. 1–6, 2015.

[13] N. E. Huang *et al.*, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. Roy. Soc. London Ser. A, Math., Phys. Eng. Sci.*, vol. 454, no. 1971, pp. 903–995, Mar. 1998.

[14] T. Wang *et al.*, "An EMD-based filtering algorithm for the fiber-optic SPR sensor," *IEEE Photon. J.*, vol. 8, no. 3, Jun. 2016, Art. no. 6803008.

[15] X. Wang, Z. Chen, J. Luo, J. Meng, and Y. Xu, "ECG compression based on combining of EMD and wavelet transform," *Electron. Lett.*, vol. 52, no. 19, pp. 1588–1590, 2016.

[16] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," *Adv. Adapt. Data Anal.*, vol. 1, no. 1, pp. 1–41, 2008.

[17] M. E. Torres, M. A. Colominas, G. Schlotthauer, and P. Flandrin, "A complete ensemble empirical mode decomposition with adaptive noise," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, May 2011, pp. 4144–4147.

[18] P. A. Delgado-Arredondo, D. Morinigo-Sotelo, R. A. Osornio-Rios, J. G. Avina-Cervantes, H. Rostro-Gonzalez, and R. de Jesus Romero-Troncoso, "Methodology for fault detection in induction motors via sound and vibration signals," *Mech. Syst. Signal Process.*, vol. 83, pp. 568–589, Jan. 2017.

[19] X. Yu, F. Dong, E. J. Ding, S. P. Wu, and C. Y. Fan, "Rolling bearing fault diagnosis using modified LFDA and EMD with sensitive feature selection," *IEEE Access*, vol. 6, pp. 3715–3730, 2018.

[20] K. Dragomiretskiy and D. Zosso, "Variational mode decomposition," *IEEE Trans. Signal Process.*, vol. 62, no. 3, pp. 531–544, Feb. 2014.

[21] M. Niu, Y. Hu, S. Sun, and Y. Liu, "A novel hybrid decomposition-ensemble model based on VMD and HGWO for container throughput forecasting," *Appl. Math. Model.*, vol. 57, pp. 163–178, May 2018.

[22] W. Liu, S. Cao, Z. Wang, X. Kong, and Y. Chen, "Spectral decomposition for hydrocarbon detection based on VMD and Teager–Kaiser energy," *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 4, pp. 539–543, Apr. 2017.

[23] W. E. Wong, V. Debroy, R. Golden, X. Xu, and B. Thuraisingham, "Effective software fault localization using an RBF neural network," *IEEE Trans. Rel.*, vol. 61, no. 1, pp. 149–169, Mar. 2012.

[24] Y. Sun, G. Xie, Y. Cao, and T. Wen, "Strategy for fault diagnosis on train plug doors using audio sensors," *Sensors*, vol. 19, no. 1, p. 3, 2019.

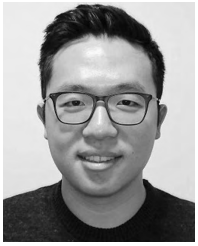
[25] D. Wang, H. Guo, H. Luo, O. Grunder, Y. Lin, and H. Guo, "Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm," *Appl. Energy*, vol. 190, pp. 390–407, Mar. 2017.

[26] X. Liu and S. C. Draper, "The ADMM penalized decoder for LDPC codes," *IEEE Trans. Inf. Theory*, vol. 62, no. 6, pp. 2966–2984, Jun. 2016.

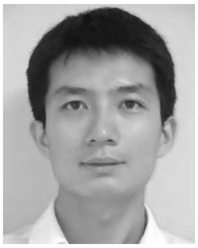
YONGKUI SUN received the B.S. degree in automation from Beijing Jiaotong University, in 2016, where he is currently pursuing the Ph.D. degree in traffic information engineering and control. His research interests include fault diagnosis and condition monitoring in train control systems.

YUAN CAO received the B.S. degree in electric engineering and automation from Dalian Jiaotong University, in 2004, and the Ph.D. degree in traffic information engineering and control from Beijing Jiaotong University, in 2011, where he currently an Associate Professor. Since 2006, he has participated in many engineering practice, especially in the signal and communication system of high-speed railway. He has taken part in several key national research projects in the field of high-speed train control systems. His research interest includes health management in train control systems.

MINGJUN ZHOU is currently an Engineer of Railway Electrification Transformation Project Construction Headquarters, China Railway Harbin Bureau Group Co., Ltd, Harbin. His research interests include health management and simulation of railway signaling systems.



TAO WEN received the B.Eng. degree from the School of Computer Science, Hangzhou Dianzi University, Hangzhou, China, in 2011, the master's degree from the Department of Electrical and Electronic Engineering, University of Bristol, Bristol, U.K., in 2013, and the Ph.D. degree from the Birmingham Centre for Railway Research and Education, University of Birmingham, Birmingham, U.K., in 2018. He is currently with Beijing Jiaotong University. His research interests include CBTC system optimization, railway signaling simulation, railway condition monitoring, wireless signal processing, and digital filter research.



PENG LI received the Ph.D. degree from the Harbin Institute of Technology, Harbin, China, in 2009. He undertook Postdoctoral Research at Beijing Jiaotong University, Beijing, China, from 2009 to 2011, and Visiting Research at the University of Melbourne, Australia, from 2013 to 2014. He is currently with the School of Electronic and Information Engineering, Beijing Jiaotong University. His research interests include automatic control, renewable energies, and transportation systems.

CLIVE ROBERTS is currently a Professor of railway systems with the University of Birmingham. He is also the Director of the Birmingham Centre for Railway Research and Education, which is the largest railway research group in Europe with just over 100 researchers. He works extensively with the railway industry and academia in Britain and overseas. He leads a broad portfolio of research aimed at improving the performance of railway systems, including a leading a strategic partnership in the area of data integration with Network Rail. His main research interests include the areas of railway traffic management, condition monitoring, energy simulation, and system integration.