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Intelligent identification of key characteristic points and its application in electromagnet operation condition monitoring of operating mechanism

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Abstract: The electromagnet's state of operation plays a crucial role in maintaining the operational mechanism of circuit breakers, as it acts as a trigger for the opening and closing action of the mechanism. However, due to the interference of complex electrical environments and the limitation of sensing conditions, there are significant deficiencies in the robust condition monitoring of electromagnets. A hybrid two-stage method was proposed to diagnose the running state of the electromagnet of the operating mechanism. By intelligently identifying the key characteristic points of the electromagnet current signal, the proposed method indirectly realized the intelligent diagnosis of the state of the electromagnet. In the first identification stage, an intelligent U-Net neural network suitable for the one-dimensional signal was proposed to realize the adaptive identification of crucial feature points via the obtained current signal of electromagnets. In the second condition monitoring stage, based on the position and the current value of the key feature points, the operating state of the electromagnet could be identified specifically. The experimental findings demonstrated that the suggested strategy was capable of successfully identifying the key characteristic points, with a near-perfect recognition success rate. The proposed method realized the adaptive identification of various electromagnet faults with only a few fault samples, which provided a guarantee for robust state identification of electromagnets and had the advantage of high interference resistance.
Key words: condition monitoring; current signal; U-Net; circuit breaker; electromagnet

0 Introduction

As a critical component in electrical power transmission and distribution, circuit breakers play a significant role in the reliability guarantee of power supply[1]. Operating mechanism is employed to maintain the continuous running of circuit breaker movement. With the engagement of electromagnetic coils, the generated electromagnetic force can push the tripping mechanism and further propel the whole circuit breakers[2]. Accordingly, robust identification of the operating status of the electromagnetic coil holds significant importance in ensuring dynamic power distribution and the healthy operation of the power grid.

As presented before, the electromagnetic coil is directly driven by the trigger current signal. As a result, the control coil current waveform may be used to represent variations in the characteristics since it provides rich information on the electromagnetic coil's operational status. Zheng et al.[3] indicated that the system states (e.g. core displacement, deformation of transmission mechanisms, contact conditions, core sticking, and coil inter-turn short circuit) might be identified from the acquired coil current waveform of the electromagnet. Ouyang et al.[4] found that the current in the solenoid coil varied with each opening and closing process, and the magnitude of the current at the location of the key characteristic points in its waveform was crucial for figuring out how well the circuit breaker operating mechanism was functioning. Liu et al.[5] obtained several key characteristic points for subsequent fault analysis by analyzing the coil current waveform during solenoid closing under standard conditions. Thus, a reliable evaluation of the opening and closing electromagnetic coils of the operating mechanism may be achieved if a mapping relationship between normal current signals and the signals to be examined can be established.

As a traditional research spot, an enormous amount of research has been done on equipment condition monitoring. The efforts can mainly be categorized into two strategies: the knowledge-driven method and the data-driven method. By extracting the feature quantities of the sampled signals with necessary signal processing approaches, the knowledge-driven method can recognize the running state accordingly. With variational mode decomposition, Zhuang et al.[6] suggested a flexible approach to extract the features contained in the coil current signals. After the decomposition, the central frequency of the empirical mode components can be obtained and the feature values of the coil current signals can also be extracted. Sun et al.[7] employed the Hilbert-Huang transform method in conjunction with the motor current signal analysis approach to detect pump cavitation and achieved high-sensitivity monitoring of cavitation state through feature extraction and signal analysis. The second strategy is the data-driven method, where models are established and trained on a large number of data samples to optimize the model. Shi et al.[8] proposed a hybrid method for spring energy storage state recognition and successfully applied it to the operating mechanism of circuit breakers. Ruan et al.[9] proposed a fault identification model based on support vector machine for accurate identification of circuit breaker faults by analyzing the coil current signal and vibration signal.

Therefore, for knowledge-driven methods, it is still not an easy task to establish a general feature extraction method due to changes in the environment and sampling conditions. On the other hand, for the data-driven method, the exitance of a large amount of balanced data in different running states is the prerequisite condition of robust identification. However, in the engineering scenarios, the equipment is generally healthy in the most time, which largely limits the performance of the intelligent models. In order to solve these problems, a hybrid-driven monitoring model was proposed[10-12].

Semantic segmentation, a typical method in computer vision, has gained attention, especially U-Net with its effective U-shaped architecture. In order to solve the problem that traditional convolutional neural networks were difficult to obtain global context information, result in subpar anomaly detection performance, Jiang et al.[13] proposed a masked swim transformer U-Net for anomaly detection and achieved superior anomaly detection and localization performance in related datasets. Cao et al.[14] introduced an improved SE-U-Net network for semantic segmentation, effectively inheriting the U-Net structure's superior learning capacity for small sample sizes. In contrast to the 2D data in semantic segmentation, the coil current signals in this research were typical 1D time-domain signals. Therefore, establishing a method to locate key points suitable for 1D signals and accurately identifying relevant features within them is crucial for achieving intelligent diagnosis of electromagnetic actuators.

Drawing inspiration from the U-Net design and the recent research of our research group[15], a hybrid two-stage method was introduced for electromagnet operation condition monitoring of the operating mechanism. In the first data-driven stage, different from the traditional semantic segmentation problem, an improved U-Net suitable for time series was established to intelligently identify the key points in a current signal of electromagnetic actuators. In the second knowledge-based stage, by exploring the movement mechanism of an electromagnet, based on the location and the degree of the key points, the operating state of the electromagnet was identified specifically.

1 Intelligent U-Net for one-dimensional signals

1.1 U-Net structure

As depicted in Fig. 1, traditional U-Net is made up of an encoder-decoder architecture. The encoder progressively uses pooling layers to decrease the spatial dimensions, and the decoder progressively restores the spatial dimensions and object features. During training, information sharing between the encoder and decoder architectures in the network is facilitated by the shortcut link (gray arrow). The stepwise decreasing encoder structure and the stepwise increasing decoder structure further improve the high dimensional spatial feature extraction ability .

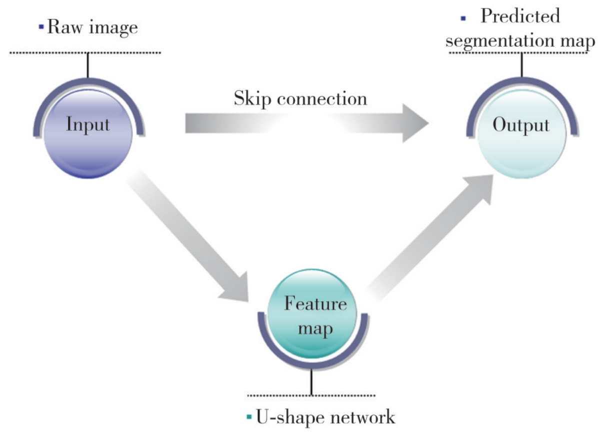


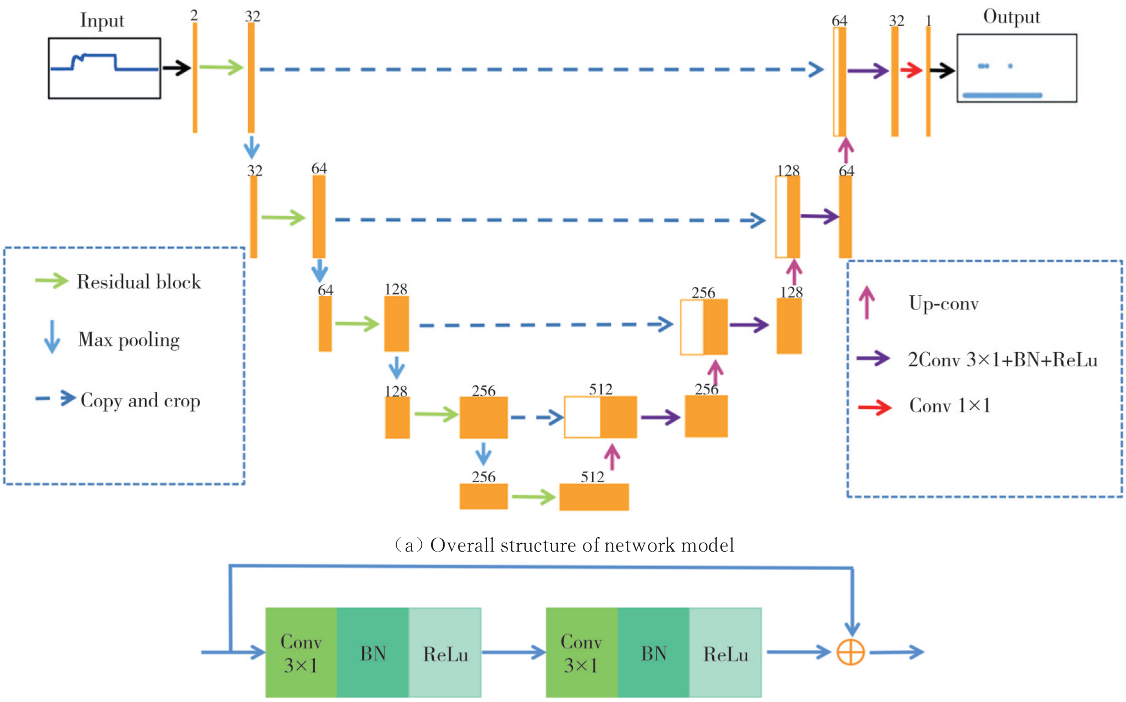
Fig. 1 Structure of traditional U-Net

The down-sampling path (the encoder structure) consists of a series of convolution, pooling, and activation layers, which are used to gradually reduce the resolution of the image and extract features. Each down-sampling layer divides the feature maps into two parts: a feature map with half the number of channels and a skip connection that is connected to the corresponding layer in the up-sampling path. These skip connections take the output of the encoding part as input to the decoding part, capturing high-level feature information that helps accurately restore the resolution of the image.

The up-sampling path (the decoder structure) is composed of a series of transposed convolutions, skip connections, and activation layers, which is used to restore the resolution of the image. In order to enhance features, each up-sampling layer expands the number of channels through convolutional layers by combining the feature maps from the preceding layer with the appropriate skip connection. Finally, a 1×1 convolution is used for dimension reduction, reducing the number of channels to a specific number to obtain the target image.

1.2 Improved U-Net for one-dimensional time-series signals

As previously mentioned, developing a key feature point localization method suitable for one-dimensional signals is crucial for running state intelligent diagnosis of electromagnets. The task seems similar to a typical semantic problem. By introducing the traditional semantic segmentation method (which is suitable for two-dimensional signals) to time-series, a point-to-point adaptive one-dimensional U-Net was proposed in the research to extract features from current signals and precisely locate the positions of key features. The proposed one-dimensional U-Net is shown in Fig.2.



(a) Overall structure of network model

(b) Residual block

Fig. 2 Structure of one-dimensional U-Net network

The network was comprised of two symmetrical pathways: a down-sampling path and an up-sampling path. In order to adapt to the feature extraction and analysis needs of one-dimensional current signals, the two-dimensional convolution and pooling operations in the original U-Net network model was replaced with one-dimensional ones. Such an adjustment allows the network to directly process time series data and capture the time-dependent features and dynamic changes in the one-dimensional current signal more effectively. Considering the specificity of one-dimensional current signals, traditional convolution-based networks (which act like filters) are not directly applicable. If the filter is used directly, the key point features are attenuated due to energy loss. Therefore, the ResNet module was introduced in the downsampling process, which enhanced the network's ability to adaptively judge changes in key features of the current signal through shortcut connections. Residual blocks, a key component of deep residual networks, were primarily designed to address the issues of vanishing gradients and model degradation during the training of deep neural networks. The residual block included a skip connection, which directly passed the input signal to the output of the block, bypassing intermediate layers. The block consisted of two convolutional layers: a ReLU activation function and a batch normalization (BatchNorm) layer after each other. The input signal to the block was processed through the first convolutional layer and activation function to produce an intermediate feature map. Subsequently, the intermediate feature map was transformed into an output signal through the second convolutional layer. Finally, the input signal was added to the output signal to obtain the final output signal. With the presence of skip connections, even if the output of the convolutional layers before the activation function is extremely small or even zero, the input signal can still be directly transmitted to the output through the skip connection. This prevents gradient vanishing and model degradation from occurring.

The expansive path consisted of up-sampling the feature maps using two transposed convolutional layers. A BatchNorm layer followed each convolutional layer to double the size of the feature maps from their initial dimensions. In the final layer, a 1×1 convolution was employed to map the feature maps to a single channel for predicting the positions of key features in the current signal.

2 Feature-based condition monitoring method of electromagnets

2.1 Movement mechanism of electromagnet

As illustrated in the introduction part, the generated electromagnetic force can propel the circuit breaker. Therefore, the current of the electromagnetic coil can be used to trace the operation status. After receiving the control circuit, the current flows through the opening and closing coil and generates the electromagnetic force. With the increase of the current, the generated electromagnetic force gradually breaks the threshold, the iron core is then moved to the corresponding actuator position. Therefore, by exploring the variation of the current, the running state of the electromagnetic might be realized.

A typical of the current waveform is plotted in Fig. 3. Based on the main key points (t_1, t_2, t_3, t_4), the waveform can be divided into four stages.

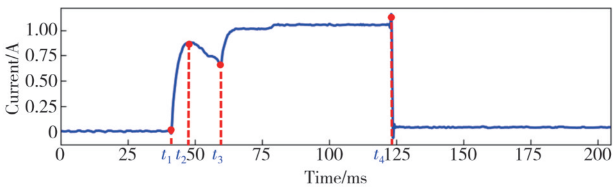


Fig. 3 Current waveform of circuit breaker coil

1) Quiescent phase (t_1—t_2)

In this phase, as theoretically analyzed above, the current signal exponentially grows accordingly. The current is still lower than the threshold. Therefore, in this phase, the iron core still stays in the original stationary position.

2) Movement phase (t_2—t_3)

During this phase, the current surpasses the threshold, the iron core starts to move at t_2. As the iron core moves, the current of the electromagnet gradually decreases until the iron core reaches its limited position. At t_3, the circuit breaker will also open or close the corresponding control circuit.

3) Current recovery phase (t_3—t_4)

After the iron core reaches its limited position, similar to the quiescent phase, the current will exponentially grow to its maximum value (the voltage value of the electromagnet is fixed in advance) throughout the entire process.

4) Disconnect phase (t_4—end)

When reaching the present disconnection time, the auxiliary switch will directly disconnect the control circuit of the electromagnet at t_4. After that, the whole actuating action of the electromagnet is finished.

2.2 Feature variation in different states

As a trigger mechanism, an electromagnet is the original power source of the control system in complex equipment. Therefore, an accurate running state of an electromagnet is crucial to maintain the health of the complex equipment. In this research, three different faulty states were investigated.

1) Turn-to-turn short circuit of the electromagnet coil

If the inter-turn short circuit occurs in the electromagnetic coil (caused by the equipment aging or mechanical wear), its corresponding electromagnet resistance will strongly decrease. Meanwhile, when the voltage applied to the electromagnet remains constant, the current will significantly increase. Therefore, its running state can be recognized by the current variation of the feature points.

2) Iron core inactivity

As analyzed above, during the operation of an electromagnet, the iron core's mobility will cause its current to change. If the iron core remains static throughout the process (due to rust or excessive load resistance), its corresponding current may be significantly different from normal conditions. According to the analysis in Section 2.1, during the quiescent phase stage, the current rapidly increases until the iron core begins to move. However, if the electromagnet is inactive, its current will directly reach its maximum value and maintain the value until the auxiliary switch cuts off the control circuit. Accordingly, in this fault state, only key feature points t_1, t_2, and t_4 can be found. Thus, the state can be evaluated based on the quantity of the recognised feature points.

3) Auxiliary switch looseness

As presented before, the auxiliary switch disconnects the electromagnetic control circuit at the present time to protect the system. However, if the auxiliary switch becomes loose, its corresponding cut-off position should fluctuate. Therefore, the diagnosis of auxiliary switch looseness can be carried out based on the changes in the cutting position (t_4).

In summary, the operating status of the electromagnet can be identified based on the locations and values of the obtained current signal's four key feature points. The algorithm proposed in this research can be summarized as follows.

Feed the acquired current signal to the established network in Section 1, after the calculation, the position of the key feature points can be intelligently acquired.

If the number of feature points is 3 and the missing characteristic point is t_3, the current value at t_2 is greater than the standard current value range, the iron core of the electromagnet may be inactive.

If the number of feature points is 4 and the current values at t_2 and t_3 are all greater than the standard range, the short circuit may have occurred in the electromagnet coil.

If the number of feature points is 4 and the position where t_4 appears is not within the standard range, the auxiliary switch of the electromagnet may be loosed.

If the number of feature points is 4 and all feature point sizes and positions are within the standard range, the electromagnet is healthy.

2.3 Post-processing strategy

Artificial networks may have multiple solution locations at feature points. A post-processing strategy was proposed to address this problem. The strategy can be simply listed as follows.

The number of predicted key feature points was calculated.

If the number of key feature points was greater than 4, the distance threshold was set, and the feature points whose distance was less than this threshold were combined into one (taking their average).

If the amount of key feature points was less than or equal to 4, keep the predicted key feature point information was retained.

3 Hybrid two-stage condition monitoring method for electromagnet operation condition monitoring

To realize the intelligent identification of the key characteristic point, a hybrid two-stage method to diagnose the running state of the electromagnet of the operating mechanism was proposed. In the first data-driven stage, an improved U-Net suitable for time series was established to intelligently identify the key points in the current signal of electromagnetic actuators. In the second knowledge-based stage, it was possible to pinpoint the electromagnet's precise operating condition. The strategy can be depicted in Fig. 4. The application steps are also described below.

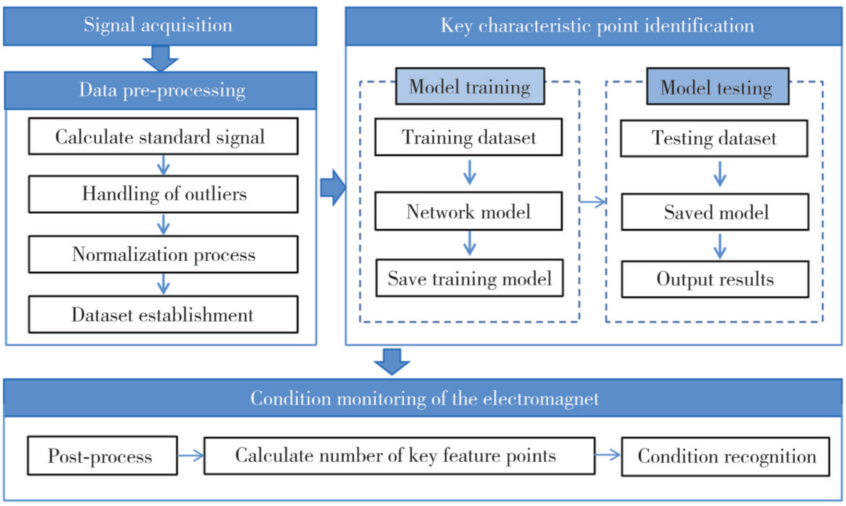


Fig. 4 Flowchart of hybrid two-stage condition monitoring method for electromagnets

After a series of opening and closing experiments of the operating mechanism, the current signals can be sampled (Section 4.1).

Calculate the standard signal based on the acquired signals (Section 4.2.2).

Suppress the noise included in the current signal based on the strategy proposed in Section 4.2.2.

After normalization, the dataset can be constructed

(Section 4.2.3).

Train the improved U-Net based on the constructed dataset (Section 4.3.1).

After the extraction of the feature signal or the processing of the acquired signal, based on the position and the degree of the key points, the condition monitoring of the electromagnet can be realized (Section 4.3.3).

4 Experiment

4.1 Experiment setup

During the experiment, Xiamen Guoyi Technology Co., Ltd.'s data acquisition system recorded the time-domain signals. A control computer, a data collecting card, and a current sensor made up the three primary parts of the system hardware. The current sensor was installed on the power leads of the circuit breaker's electromagnetic coil to measure the current signals generated during the operation of the operating mechanism. These signals were then output to the data acquisition card. The primary function of the data acquisition card was used to convert the analog signals into digital signals for ease of data processing. The control computer was used to store the collected current signals. In this experiment, a fixed sampling frequency (20 kHz) was employed to collect the current signals from the opening and closing coils, which were subsequently used for further analysis.

4.2 Dataset establishment

4.2.1 Standard signal acquisition

Caused of the complex electromagnetic and the various coupling environments, the sampled current signal was polluted by some strong noise. Besides, the strong interference seemed irregular. To accurately identify the strong noise, it is crucial to acquire a standard signal.

By calculating the average of the current signals, the standard signal was acquired. As can be seen in Fig.5, the colored area indicated the boundary of the current signal, and the solid blue line was the average standard signal.

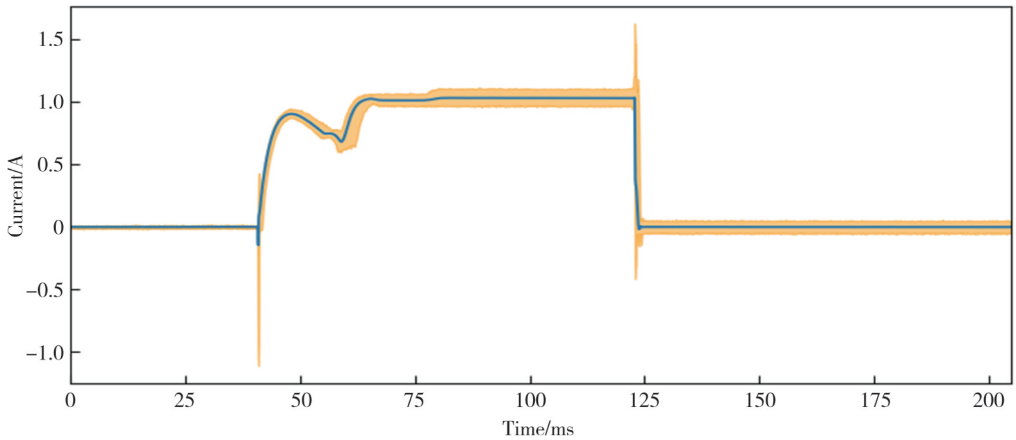


Fig. 5 Standard signal acquisition

4.2.2 Noise suppression

After acquiring the standard signal, the noise might be accurately identified. In this section, an outlier identification and suppression method based on standard signals was proposed. The main process was presented as follows.

Subtracting the acquired raw signal (Fig. 6(a)) from the average standard signal (Fig.5), the difference could be acquired (Fig.6(b)).

If the difference was greater than the average of the entire sequence of differences, this point might be an outlier.

Replacing the outlier with its neighboring point, the noise could be suppressed accordingly (Fig. 6(c)). The step can be represented as

$$\hat{x}_i=\begin{cases} x_i, & dif\_x_i \leqslant \overline{dif\_x}, \\ x_{i-1}, & dif\_x_i > \overline{dif\_x}, \end{cases} \tag{1}$$

where i is the sampling index; $\hat{x}_i$ is the noise suppressed signal; dif_x_i is the calculated difference sequence; $\overline{dif\_x}$ is the average calculation symbol.

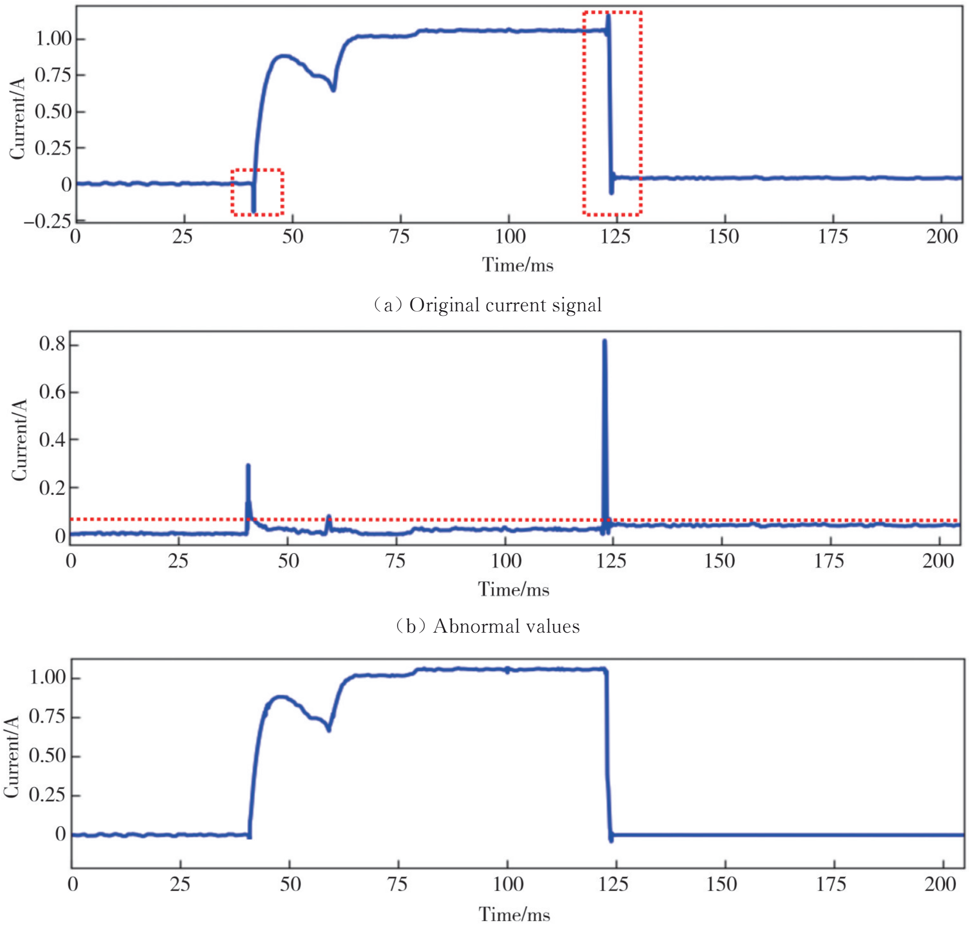
4.2.3 Data normalization and dataset construction

After suppressing the noise contained in the current signal, the signal can be normalized as

$$\tilde{x}_i=\frac{\hat{x}_i-\min \hat{x}}{\max \hat{x}-\min \hat{x}}, \tag{2}$$

where $\hat{x}$ is the noise suppressed signal; $\tilde{x}$ is the normalized signal. After the normalization, the current signal is normalized into range [0, 1].

The proposed improved U-Net suitable for one-dimensional time series was a type of semantic network. Therefore, it was necessary to acquire the state of all the sampled points. By manually annotating the positions of feature locations, the label of the dataset was acquired. In this research, 1 represented the positions of key features, while 0 represented another state. In the whole experiment, a dataset with 500 current signal samples was acquired.



(a) Original current signal

(b) Abnormal values

(c) Processed current signal

Fig. 6 Abnormalities suppression

4.3 Performance

4.3.1 Model training

Separating the established dataset into test and training sets (the ratio is 4 : 1), the model constructed in Section 2 could be trained. The weights were calculated and adjusted by the Adam optimizer throughout the model training procedure. The batch size during the training process was 32. The loss function utilized for network training was the Huber loss. The loss and accuracy during the training process are revealed in Fig.7. It illustrated that the network was well-trained. The network parameters associated with the lowest loss value in the training set were selected as the optimal model parameters. The model weights were saved for subsequent predictions.

4.3.2 Model validation

In order to assess the network model's performance, intersection over union (IoU) was used as the main evaluation metric, whose value indicated the degree of overlap between the true and predicted masks of the key feature points of the current signal. The prediction results in this study were categorized into four types: TP (true positive), TN (true negative), FP (false positive), and FN (false negative). As shown in Fig.8, label is the real current signal key feature point, and pre is the predicted current signal key feature point, then TP is the key feature point predicted as a key feature point, TN is the non-key feature point predicted as a non-key feature point, FP is the non-key predicted as a non-key feature point, FN is the key feature point predicted as a non-key feature point. Thus, the IoU can be formulated as

$$IoU = \frac{TP}{TP + FP + FN}. \tag{3}$$

As shown in Fig.9, The IoU distribution histogram of the neural network model proposed in this paper is drawn on the test set. This evaluation metric was used to judge whether the network model in this study could accurately predict the key features of the current signal.

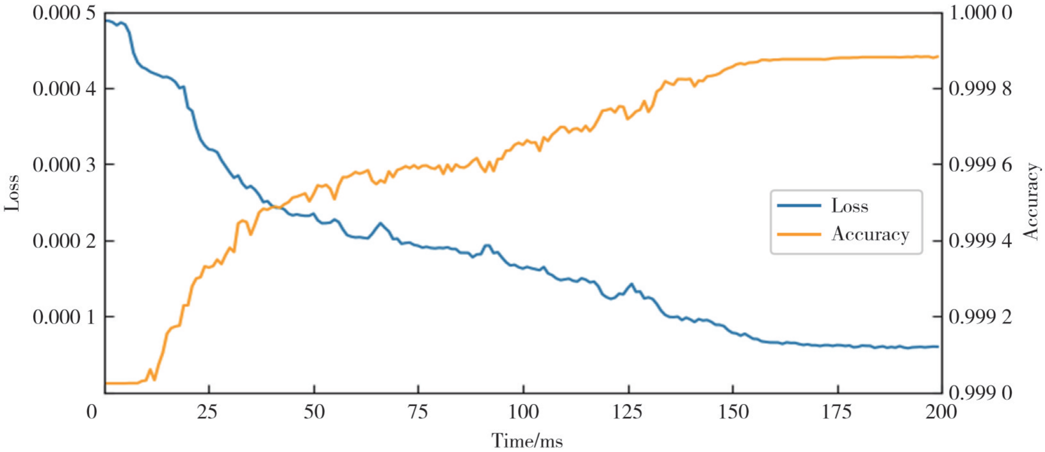


Fig. 7 Results of proposed method

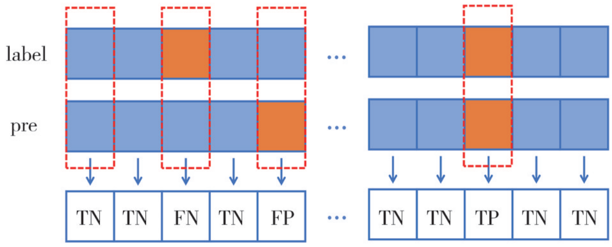


Fig. 8 Illustration of time-series IoU

By calculating the IoU values of 100 sets of test data, the average IoU of the model was 74.94%, indicating that the model had good performance in predicting key features of the current signal.

In the presentation of the predicted results, the blue bars in Fig. 10 represent the theoretically expected four key features within the given current signal. However, the computational output from the neural network reveals more than four potential features, as indicated by the red bars in Fig. 10. Consequently, to rectify these outcomes, a post-processing strategy has been implemented. This strategy aims to sift through the network outputs to identify the most meaningful features, ensuring the accuracy and reliability of the results. The operational steps and implementation details are elaborated upon in Section 2.3.

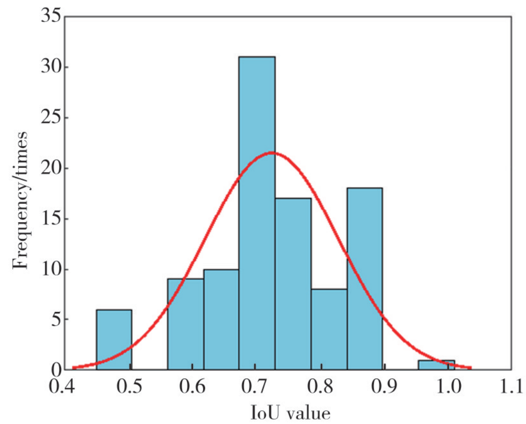


Fig. 9 Histogram of IoU frequency distribution

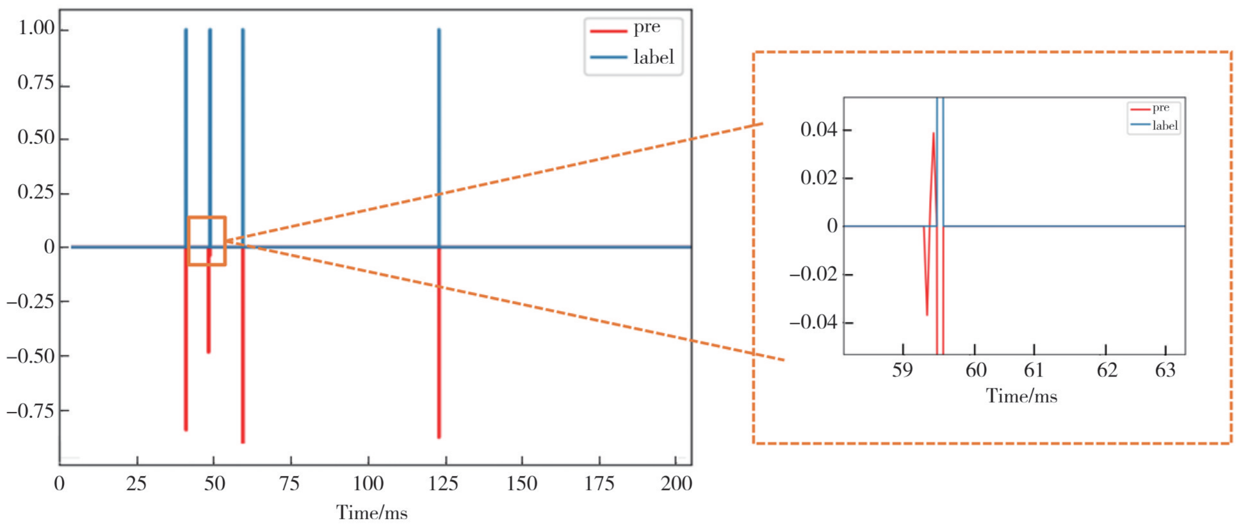


Fig. 10 Results of testing signal

4.3.3 Performance evaluation

To assess the precision of this approach in the electromagnet condition monitoring of the actuating mechanism, a confusion matrix was used to evaluate its generalization ability.

100 different sets of current signals were tested, and the results are shown in Fig.11, where the genuine label is indicated by the vertical direction and the predicted label is indicated by the horizontal direction. Category A represents electromagnet is healthy, category B represents the iron core of the electromagnet may be inactive, category C represents the auxiliary switch of the electromagnet may be loosed, and category D represents the electromagnet turn short circuit. Through the results of the confusion matrix, it indicated that the proposed method has reached 100% accuracy in the evaluation.

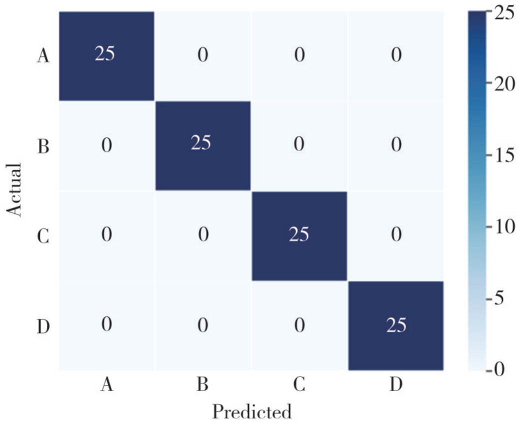


Fig. 11 Confusion matrix

5 Discussion

5.1 Influence of abnormal current interference

As presented before, the inevitable interference might influence the condition monitoring effect. In this research, the superiority of the proposed noise suppression was investigated (as can be seen in Section 4.2.2). Table 1 illustrates the result comparison. With the noise suppression strategy, the performance of the proposed method (IoU) was improved from 75.54% to 74.94%.

Table 1 Result comparison of abnormal current interference

Condition	IoU/%
With noise suppression	75.54
Without noise suppression	74.94

5.2 Influence of loss function

The loss function tends to assess the extent to which the neural network's predictions deviate from the underlying truth value. It has demonstrated that selecting an appropriate loss function plays a pivotal role in shaping the process of training and optimizing the performance of neural networks.

For a regression problem, commonly used loss functions consist of mean squared error (MSE), mean absolute error (MAE), or Huber loss. These loss functions are used to quantify the error between predicted data and the original data.

For a batch of data $D(x,y)$ containing n samples, where x represents the neural network's output and y represents the ground truth data, MSE loss is defined as

$$MSE=\frac{1}{n}\sum_{i}^{n}(x_i-y_i)^2. \tag{4}$$

The definition of MAE loss is

$$MAE=\frac{1}{n}\sum_{i}^{n}|x_i-y_i|. \tag{5}$$

The definition of Huber loss is

$$L_\delta(x,y)=\begin{cases}\frac{1}{2}(x-y)^2, & |x-y|\leqslant\delta,\\ \delta|x-y|-\frac{1}{2}\delta^2, & |x-y|>\delta.\end{cases} \tag{6}$$

Huber loss is a combination of MSE (L2 loss) and MAE (L1 loss), and it includes a hyperparameter δ. The value of δ determines the emphasis of Huber loss on L1 loss and L2 loss. Therefore, Huber loss combines the advantages of both MSE loss and MAE loss, reducing sensitivity to outliers, mitigating overfitting to some extent, and maintaining differentiability throughout. In the proposed model training process, Huber loss was chosen as the loss function with a δ value of 1. The experimental results for these three loss functions are summarized in Table 2, and Huber loss was observed to perform best in training.

Table 2 Results comparison of loss functions

Loss function	IoU/%
Huber loss	74.94
MAE loss	49.95
MSE loss	71.52

5.3 Influence of network model

In order to improve the network's ability to adapt to changes in key features, the ResNet module was applied in the downsampling path. The proposed model had better recognition performance compared to the original 1D U-Net model, and the specific experimental results are shown in Table 3.

Table 3 Result comparison of network model

Condition	IoU/%
Proposed model	74.94
1D U-Net	72.62

6 Conclusions

Data-driven and knowledge-based approaches were fused to propose a two-stage framework for condition monitoring of electromagnets. In the first stage, a data-driven method was established to intelligently identify the key points in the current signal of electromagnetic actuators. In the second stage, a knowledge-based operating state identification of electromagnets was proposed.

An upgraded U-Net suitable for time series was established to intelligently identify the key points in the current signal of electromagnetic actuators. The effectiveness of the proposed method was verified in a laboratory dataset, and the experimental results showed that the recognition success rate of the proposed strategy was almost 100%.

However, due to the limitations of laboratory conditions, there are still uncertainties due to the neglect of the synchronization of three-phase circuit breakers. Integration and optimization of monitoring methods through practical applications will be included.

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Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

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关键特征点的智能识别及其在操动机构电磁铁运行状态监测中的应用

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摘　要： 作为断路器操作机构开合动作的触发器，电磁铁的工作状态对于确保操作机构的工作状态具有重要意义。然而，由于复杂电气环境的干扰和传感条件的限制，电磁铁的鲁棒性状态监测存在很大的不足。本文提出了一种两阶段混合方法来诊断运行机构电磁铁的运行状态。该方法通过智能识别电磁铁电流信号的关键特征点，间接实现对电磁铁状态的智能诊断。在第一识别阶段，提出了适合一维信号的智能U-Net神经网络，通过获取的电磁铁电流信号实现关键特征点的自适应识别。在第二个状态监测阶段，根据关键特征点的位置和电流值，可以具体识别电磁铁的运行状态。实验结果表明，所提出的方法能有效识别关键点，识别成功率接近100%。所提出的方法只需少量故障样本就能实现对各种电磁铁故障的自适应识别。因此，所提出的方法为电磁铁的稳健状态识别提供了保障，并具有抗干扰性强的优点。

关键词： 状态监测；电流信号；U-Net；断路器；电磁铁

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