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Fault Detection of Permanent Magnet Synchronous Motor Based on Deep Learning Method

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***Abstract* —This paper proposes a deep learning algorithm for motor fault detection. Based on the Long Short-Term Memory (LSTM), one of the deep learning algorithm, catching the three-phase current values and the information of electrical angle in the previous sampling instants, the three-phase current value at the next sampling instant can be predicted in real time; the predicted error is not affected by torque fluctuations. Therefore, the operating status of the motor can be observed in real time. The simulation results show that the error waveform amplitude is very small when the motor is running normally with the load torque randomly fluctuating, and the error amplitude will increase sharply when the motor is going to be broken down.**

***Keywords*—PMSM, deep learning, fault detection, LSTM**

I. Introduction

Permanent magnet synchronous motors have high efficiency, high power density, and are widely used in various drive fields. However, when the motor is under short-circuited, open circuit, or other operational failure, it will produce a serious impact on the drive system. If the motor faults can be detected and take necessary measures at the moment of motor failure or even before the fault occurs, the impact of motor faults will be reduced.

The traditional fault detection method is based on the scheme of the physical structure model, and the fault is judged by detecting the current signal, the voltage signal, and the vibration and noise of the motor. These methods can achieve good detection results under ideal conditions, but have poor anti-interference ability and are easily affected by the motor parameters and operating conditions [1-6].

With the development of signal analysis technology, some strategies of extracting information from signal processing were proposed[7]. The typical method is to perform amplitude-frequency conversion and extract fault signals to determine whether a fault has occurred. However, this method is easily disturbed by external interference, and it is easy to miss detection and lead to false detection. In the process of amplitude-frequency conversion, the sampling frequency needs to be higher than twice the signal frequency. This means that a large amount of sample data is required to calculate and judge during the calculation process, which increases the computational workload and memory consumption. [8-9].

In recent years, the rapid development of artificial intelligence technology has provided a new approach to fault detection technology. Detection schemes such as fuzzy algorithms, expert systems, and neural networks have higher accuracy and anti-jamming capability. However, the large amount of computation and the lack of data samples is the difficulty of these solutions [10-14]. On the other hand, traditional artificial neural networks cannot mine useful information from acquired current signals and position signals because these signals are time-varying. An artificial neural network model that can extract information from sequence signals must be used to solve the above problems.

This paper presents a deep learning algorithm based on a recurrent neural network. By inputting a time-varying signal sequence and performing a cyclic calculation of the neuron in the recurrent neural network, the algorithm can deeply mine the information in the time-varying signal sequence and finally obtain the output. This method can obtain useful information from a few sampling period signals, and has strong anti-interference ability.

II. Current Values Prediction by LSTM

A. Traditional Neural Network

The traditional neural network model is generally made up of three parts: the input layer, the hidden layer and the output layer. Many nodes are included within each layer, and the function of these nodes is summing up the output with a set of weights from upper-layer, passing through the activation function, and delivering the data to the next layer. Calculating through fully-connected nodes from multiple layers, output is obtained from the activation function. Model of traditional fully-connected neural network is as follows:

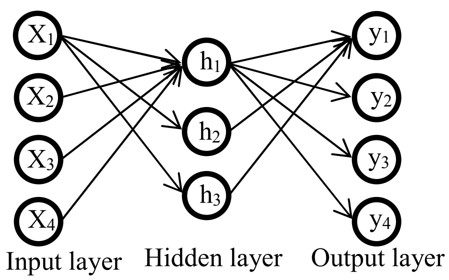

Fig. 1. The model of fully connected neural network

Calculating equations of each node is listed below:

$$
\begin{aligned}
h_k &= f_1\left(\sum_{i=1}^{n} w_{ki} x_i + b_k\right) \\
y_{\mathrm{m}} &= f_2\left(\sum_{i=1}^{n} w_{mi} h_i + b_m\right)
\end{aligned}
\tag{1}
$$

Where the f1, f2 are activation function, and usually this function is set to be linear function $f(x) = x$, or sigmoid function : $\sigma(x) = \frac{1}{1+e^{-x}}$.

In the neural network training process, lots of training sample (input ***x***) and sample label (desired output ***y***) are required to provide the reference. Sets of weight ***w*** and bias ***b*** are adjusted continuously to learn a general rule that maps input to output, actually this is a process of function fitting. After completing the training process, the corresponding predicted output (***y_pred***) can be gained by inputting the actual value ***x***.

However, some specific problems cannot be solved by adopting the model of traditional neural network, like, acquiring information from time-varying signals or predicting the variety of signals. The reason is that all the input data are assumed to be independent with each other in the traditional neural network model, and there is no direct connection of the nodes in the input layer, so the time-varying information which is of great importance cannot be extracted. Besides, calculating all the signal values sampled before will significantly increase the calculation work.

B. Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) provides an effective solution to the problem of mining the information from time-varying signals. Due to its ability of taking advantage of time-varying information by remembering sequence input, this model has been widely used in natural language processing (NLP), neural text generation, speech recognition and so on[15]. Time-varying information is of great importance during the process of signal analyzing, so it is feasible to adopt RNN model to analyze the electrical signals.

The obvious distinction between traditional neural network and RNN is that there is a loop in the RNN model, which enables the model to remember the information and take it to the calculation of next time step. The model of RNN is as follows:[15]

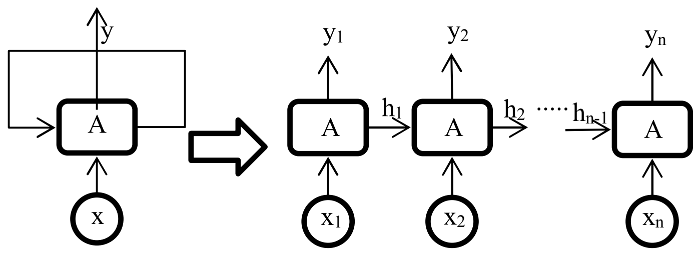

Fig. 2. The model of Recurrent Neural Network (RNN)(left) and the folded model of RNN(right)[16]

Where $\vec{x}_1, \vec{x}_2 ... \vec{x}_n \in R^N$ are input in time sequence.

At each time step the calculation are as follows:

$$\begin{aligned} \vec{h}_t &= f(\mathrm{W}_1 \cdot \vec{x}_t + \mathrm{W}_2 \cdot \vec{h}_{t-1} + \vec{b}) \\ \vec{\mathrm{y}}_t &= \vec{h}_t, (\mathrm{t} = 1,2 ... n, \vec{h}_{-1} = 0) \end{aligned} \tag{2}$$

Where $\mathrm{W}_1 \in R^{M \times N}, W_2 \in R^{M \times M}$ are weights for the input at the time step t and weights for the recurrent input. ***f*** is the activation function, usually set as hyperbolic tangent function : $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$.

It can be seen from the calculation process that the output of the last instant is the input of the next instant, and this makes the information of sequence to be transferred to the next calculation step rather than be discarded immediately. In RNN, the input signals of each instant are preserved during the recurrent calculation process, and the information of the time order relation is well preserved too.

C. Long Short-term Memory (LSTM)

However, the RNN also has its limitations. The main drawback is that it is difficult to process long sequences. When the sequences is too long, RNNs usually are difficult to be trained because the gradient vanishing (***W***<1) and gradient exploding (***W***>1)[17-18]. In order to address these problems, the Long Short-term memory (LSTM) is developed, which can be used to judge whether information aforementioned should be remembered or not in each loop. The model of LSTM is as follows:

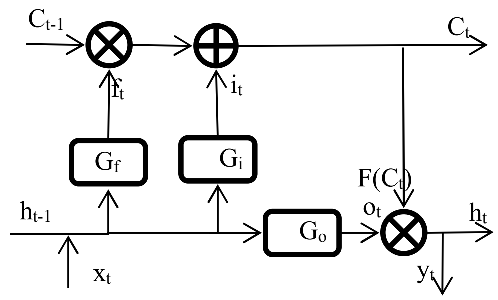

Fig. 3. The model of Long Short-term Memory (LSTM) unit[16]

It can be seen from the model that a common architecture of LSTM unit is composed of 2 information flows and 3 gates. Flow ***h*** is output flow, which can output the result and join in the calculation with the input in the next time step; Flow ***C*** is memory flow, which can modify or maintain the information during the calculation; $\boldsymbol{G_i}$ is the Input Gate, which control the information that should be maintained; $\boldsymbol{G_f}$ is the Forget Gate, which control the information that should be forgotten; $\boldsymbol{G_o}$ is the Output Gate, which control the information that should be output. The equations for the forward pass of an LSTM unit are as follows:

$$\begin{cases} C_t = C_{t-1} * f_t + i_t \\ y_t = h_t = o_t * F(C_t) \\ f_t = \sigma(W_f \bullet [h_{t-1}, X_t] + b_f) \\ i_t = [\sigma(W_i \bullet [h_{t-1}, X_t] + b_i)] * \\ \qquad F(W_c \bullet [h_{t-1}, X_t] + b_c) \\ o_t = \sigma(W_o \bullet [h_{t-1}, X_t] + b_o) \end{cases} \tag{3}$$

Where F is activation function, which is usually set as hyperbolic tangent function: $\tanh(x)=\dfrac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$. LSTM adds judgment process in every recurrent calculation to decide whether to retain the information or not, which prevents gradients vanishing or gradients exploding.

The idea of the fault detection algorithm is to predict the current value in the next sampling instant by detecting the three-phase current values and the information of the rotor position in the previous several sampling instants. Comparing the predicted current value of the networks output with the actual value, if the error suddenly increases, then motor fault can be confirmed. Besides, fault detection based on LSTM can greatly reduce the disturbance of external torque, thus reduce the miss-detection rate and false-detection rate effectively.

III. GET SAMPLE DATA AND TRAIN

In this paper, three-phase current value and rotor position information in several consecutive sampling instants are collected to be built into several sequences which is input to the LSTM in turn. After finishing the input of sequences, the final output value is obtained to pass through the fully-connected neural network, and the output of the network is the predicted three-phase current value in the next sampling instant.

In order to obtain a robust LSTM and eliminate the interference of motor acceleration, deceleration or torque ripple, etc., waveforms of current and information of rotor position at various operating states (different speed or different load torque) should be collected as training samples, and then the trained LSTM can be imported into Simulink for current prediction.

IV. SIMULATION RESULTS

Simulation analysis is implemented in MATLAB/Simulink software. The parameters of the PMSM are given in the table1.

Set the load torque to 6.8N • m with torque disturbance of ± 3N • m.

TABLE I. PARAMETERS VALUES

Parameter	value
rated voltage, U_N	270V
rated speed, n_N	2000rpm
rated torque, T_N	12N • m
stator phase resistance, R_s	0.129 Ω
d-axis inductance, L_d	4.02e-3H
q-axis inductance, L_q	3.77e-3H

A. Simulation of Instantaneous Fault

Ideally, open and short circuit faults in the motor system are always completed instantaneously. The simulation of this kind of failure can be achieved by connecting infinite resistance or instantaneous grounding at a certain moment.

A single-phase open circuit fault is assumed to happen at t=0.5s. The current waveform and prediction error waveform show as follows:

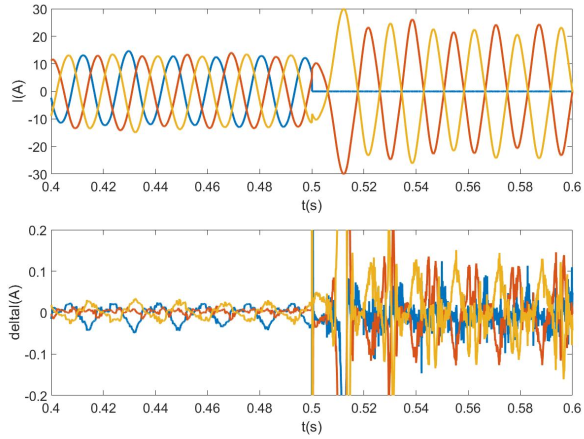

Fig. 4. Current waveform (up) and prediction error waveform(down) with torque disturbance. A single-phase open circuit fault is assumed to happen at t=0.5s

A single-phase short circuit fault is assumed to happen at t=0.5s. The Current waveform and prediction error waveform show as follows:

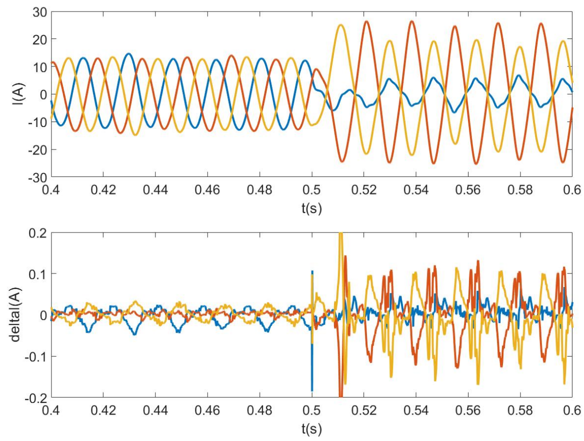

Fig. 5. Current waveform (up) and prediction error waveform(down) with torque disturbance.A single-phase short circuit fault is assumed to happen at t=0.5s.

From the current waveform and the prediction error waveform, it can be found that although the input torque is constantly changing, the prediction error is always within ± 0.05A when the motor operate normally. When the fault occur at t=0.5s, the prediction error increases rapidly, and maintains at a large value, which can be used to detect the fault in time.

B. Simulation of Gradual Faults

Under actual conditions, the open circuit and short circuit faults of the motor system take some time to complete. This failure can be simulated by inserting a resistor whose resistance changes exponentially with time.

Connect an external resistor in series with the power bus at t=0.5s, the resistance of the resistor increases exponentially with time.

The actual current waveform is shown in Fig.6. If the current threshold is set to be 10A, the fault signal is detected until t=0.82s.

Fig.7 shows the prediction error waveform. The threshold is set to be 0.05 and the error warning signal can be detected at t=0.793s, at which time the current waveform remains unchanged.

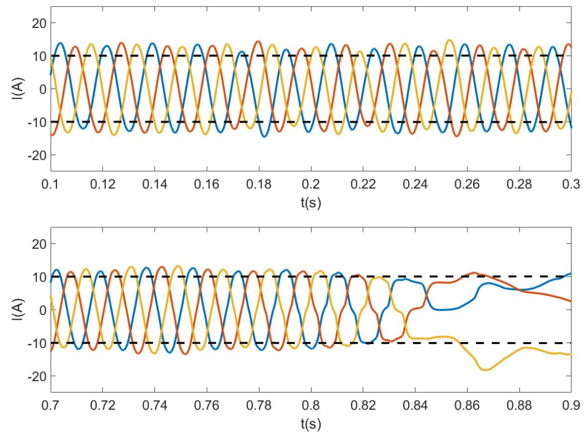

Fig. 6. Current waveform during normal operation(up) and after error occurred(down) with torque disturbance

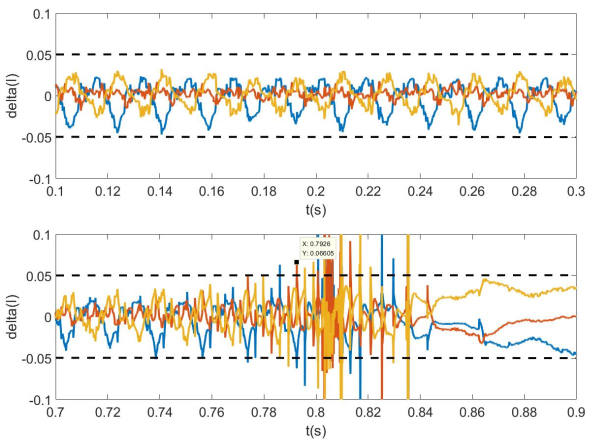

Fig. 7. Prediction error waveform during normal operation(up) and after error occurred(down) with torque disturbance

From the current waveform and the prediction error waveform, it can be seen that although the input torque is constantly changing, the prediction error is always within ± 0.05A when the motor operate normally. When the fault is about to occur, the prediction error waveform changes significantly earlier than the current waveform, which proves that the LSTM algorithm can be used for motor fault detection and has good anti-interference ability.

C. Simulation of Early Faults

In the event of an early motor failure, the winding resistance will increase, or the insulation of the windings will decrease. An early failure of the motor can be simulated by adding a relatively small resistance to the winding at a certain time or a large resistance to ground.

Assume that a 10 Ω resistor is connected to the winding in series at t=0.5, the waveform is shown as follow:

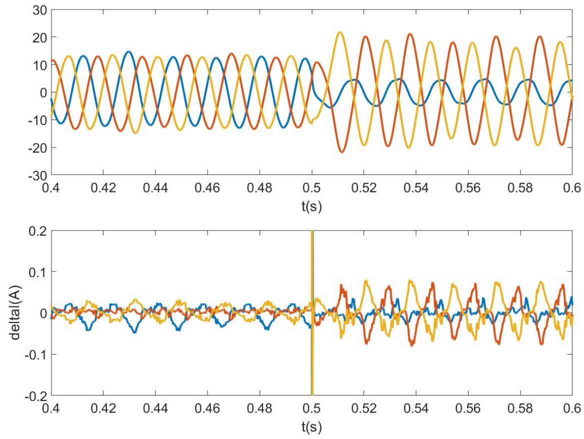

Fig. 8. Current waveform (up) and prediction error waveform (down) with torque disturbance. A 10 Ω resistor is connected to the winding in series at t=0.5s

If the winding-to-ground resistor decreases to 0.0005 Ω at t=0.5, the waveform is as follow:

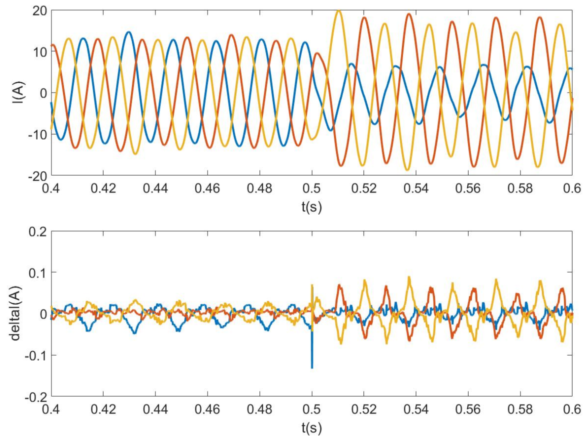

Fig. 9. Current waveform(up) and prediction error waveform(down) with torque disturbance. The winding-to-ground resistor decreases to 0.0005 Ω at t=0.5s

From the waveform diagram, it can be seen that the motor can continue to work in the early fault. But in the error waveform diagram, it can be seen that the amplitude of the waveform has exceeded the threshold, and the fault can be judged in time.

D. Simulation of Anti-interference Ability

The detection strategy based on LSTM model has strong anti-interference ability. During the simulation, the robustness of the algorithm is verified by suddenly increasing or reducing the load at a certain time and changing the load continuously during the work process.

At first the load torque is set to 4.2N • m with torque disturbance of ± 3N • m. If the load torque changes to 7.2N • m at t=0.4s and then decreases to 1.2 N • m at t=0.6s, the waveform is shown as follow :

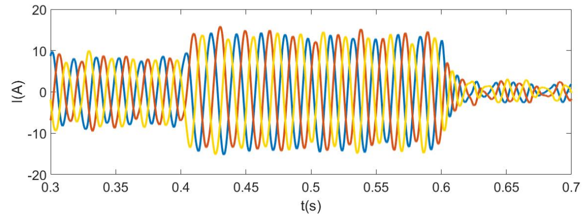

Fig. 10. Current waveform

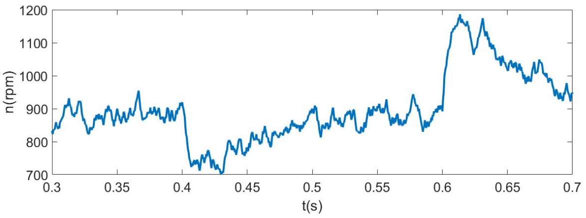

Fig. 11. Speed waveform

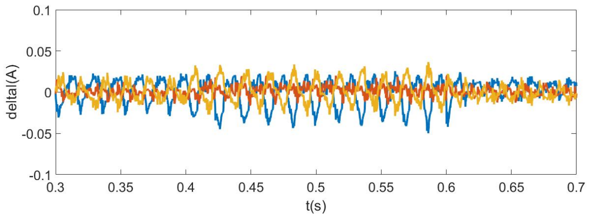

Fig. 12. Prediction error waveform

It can be seen from the waveform diagram that there is a great change in the three-phase current under the external strong interference and the load condition, and the speed also changes at this stage. However, the amplitude of the predicted current is still very small. It can be found that the predicted current error is not disturbed by external torque changes.

V. CONCLUSION

This paper presents a deep learning algorithm for motor fault detection. The RNN/LSTM model is used to analyze the data of the detected three-phase current and rotor position, and the useful information in these time-varying signals is extracted to detect faults. The simulation results verify the effectiveness of the method. Compared with the traditional fault detection method, the deep learning-based fault detection method requires less sampled data, the calculation process is modular, easy to integrate, and has strong anti-interference ability. It has a good application prospect in the field of permanent magnet synchronous motor fault detection.

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