Fault Prediction of Electromagnetic Brake Based on AINN and Grey MGM(1,n) Model

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Abstract. In order to predict the possible fault points of electromagnetic brake, a novel combined diagnosis model based on multivariable grey prediction model MGM(1,n) and adaptive integrated neural network (AINN) was proposed in this paper. MGM(1,n) model was used to predict the development trend of multiple groups of fault feature factors. Then by Fuzzy C-mean (FCM) algorithm, cluster analysis on the predicted results from MGM(1,1) was performed, and in turn, clustering results feed into of AINN to predict and identify fault features. To verify the performance of the combined model, a case of electronic brake fault diagnosis is given, and the model analysis consisting of 8 possible faults is carried out, finding that the proposed combined model has better fault identification capacity with better convergence and less error, showing stronger promotional practical value.

Keywords: Fault prediction; MGM (1, n); Electromagnetic brake; AINN.

1. Introduction
Electromagnetic brakes play an important role in machine, elevator, packaging, building, mining and so forth [1]. Accordingly, it has significance for fault prediction and diagnosis of electromagnetic brake. Therefore, it is important to find the possible faults in running process of the electromagnetic brake timely in order to maintain the stability and reliability of the electromagnetic brakes [2, 3].

With the rapid development of the Artificial Intelligence (AI), some new methods can be employed to serve fault prediction and diagnosis of electromagnetic brake [4]. Such as artificial neural network (ANN), has been applied in fault prediction domains widely so far [5, 6]. However, sometimes it is hard to obtain enough characteristic parameters of the electromagnetic brake. Fault information of the electromagnetic brake is incomplete showing grey characteristics. Hence, grey prediction theory can be adopted to forecast the variation trends of the fault parameters of the electromagnetic brakes [7, 8]. Rare researches by combining them together can be found till now.

In this work, a novel combined model is proposed by integration of MGM (1, 1) and AINN to predict the possible faults of the electromagnetic brake.

2. Adaptive Integrated Neural Network
Adaptive integrated neural network (AINN for short) combines outputs of various ANN together. It focuses on samples training, determination of integration scale and interrelated methods. Nowadays, one or two separate studies of above three contents are conducted by researchers [9]. However, a separate study on one or two items cannot guarantee the prediction effects for integration of multiple...
ANNs is significantly different from separate contents. Therefore, it is urgent to put forward a new algorithm to regulate integration weight adaptively according to different input data.

2.1. Sample Clustering Based on Fuzzy C-means Algorithm
In our work, Fuzzy C-means (FCM) algorithm [10] is employed to cluster the training samples of the individual network. Given training sample $X = \{X_1, X_2, \ldots , X_n\} = \{(x_1, d_1), (x_2, d_2), \ldots , (x_n, d_n)\}$, in which $x_i$ denotes input sample, $d_i$ is output expectation, and $n$ is the number of samples. The characteristics of input sample are given as $x_i = \{x_{i1}, x_{i2}, \ldots , x_{in}\}$, in which $k$ is the number of characteristics, i.e., the number of neurons of input layer of ANN. Algorithm of FCM is as follows.

(1) To meet the requirements of FCM, the range criterion is given as $i x \bar{=} \frac{x_i - x_{ij}}{R_j}$, where $x_{ij}$ denotes the center of the cluster, $d_{ij}$ is the member degree of sample $i$ belonging to cluster $j$.

(2) For given error threshold $\varepsilon$ and iterative steps $n$, If $\|D^{(n)} - D^{(n+1)}\| < \varepsilon$, then terminate and exit, else go to step (2).

2.2. Adaptive Integrated Neural Network and Its Algorithm
In our work, adaptive integrated neural network (abbreviated as AINN) is provided, whose principle is shown in Figs.1-2.

Assume the samples are divided $p$ categories $X_1, X_2, \ldots , X_p$ with $c_1, c_2, \ldots , c_p$ as the centers, in which $c_j = (c_{j1}, c_{j2}, \ldots , c_{jn})$, $0 < j < p$. Let $d = \{d_1, d_2, \ldots , d_n\}$ be the input of the sample, the distance between $d$ and the category $j$ is

$$\text{diff}(d, c_j) = \sum_{i=1}^{n} |d_i - c_{ij}|, 0 < j < p.$$  \hspace{1cm} (2)

Integrated weight $w_j$ is
\[ w_j = \frac{\text{diff}(d, c_j)}{\sum_{j=1}^{p} \text{diff}(d, c_j)}, 0 < j < p. \]  

where \( w_{ij} \geq 0, \sum_{j=1}^{p} w_{ij} = 1 \). If \( V_j \) is the output of the individual NN, the output of AINN can be represented as \( V = \sum_{j=1}^{p} w_j V_j \). The algorithm of AINN can be summarized as follows:

1. Establish the training sample of the individual network by FCM.
2. Training the individual neural network NN \( i, i=1,2,\ldots,n \).
3. Calculating the similarity degree \( \text{diff}(d, c_j) \) and the integrated weight \( w_j \) as shown in Eqns (2-3).
4. Testing the AINN algorithm. If it meets requirements, it jumps to (5), or else to (1).
5. Forecasting the occurrence of failures.

3. MGM(1, n) Model

Aiming to multiple parametric predictions, MGM(1, n) model provides an effective method to forecast the evolutionary trend of the decisive objective. This model is a 1\(^{\text{st}}\) order differential equation with \( n \) variables and has been used in many domains today.

For \( n \) original data sequences \( x_i(0)(k), i=1,2,\ldots,n, k=1,2,\ldots,m \), obtain their 1-AGO sequences by \( x_i(0)(k) = \sum_{j=1}^{k} x_i(0)(j) \). Let \( X^{(1)}(k) = [x_1^{(1)}(k), x_2^{(1)}(k), \ldots, x_n^{(1)}(k)]^T \), then, the shadow equation of MGM (1, \( n \)) can be expressed as such:

\[
\frac{dX(t)}{dt} = MX^{(1)}(t) + N
\]

where, \( M \) and \( N \) are two undetermined parameter matrices with the following forms.

\[
M = \begin{bmatrix}
    a_{11} & \cdots & a_{1n} \\
    \vdots & \ddots & \vdots \\
    a_{n1} & \cdots & a_{nn}
\end{bmatrix}, \quad N = [b_1, b_2, \ldots, b_n]^T
\]

The ordinary least square method can usually be employed to solve the estimators of \( M \) and \( N \). Let \( A = (A_1, A_2, \ldots, A_j, \ldots, A_n, 1), B = (B_1, B_2, \ldots, B_1, \ldots, B_n, 1) \), where

\[
A_j = \begin{bmatrix}
    \frac{(x_j(1)(2) + x_j(1)(1))}{2} \\
    \frac{(x_j(1)(3) + x_j(1)(2))}{2} \\
    \vdots \\
    \frac{(x_j(1)(m) + x_j(1)(m-1))}{2}
\end{bmatrix}, \quad B_i = \begin{bmatrix}
    x_i(0)(2) \\
    x_i(0)(3) \\
    \vdots \\
    x_i(0)(m)
\end{bmatrix}
\]

then the estimator of \( a_i = (a_{i1}, a_{i2}, \ldots, a_{im}, b_i) \) is \( \hat{a}_i = (A^T A)^{-1} A^T B_i \). The estimators \( \hat{M} \) and \( \hat{N} \) of \( M \) and \( N \) can be obtained respectively, i.e.,

\[
\hat{M} = \begin{bmatrix}
    \hat{a}_{11} & \cdots & \hat{a}_{1n} \\
    \vdots & \ddots & \vdots \\
    \hat{a}_{n1} & \cdots & \hat{a}_{nn}
\end{bmatrix}, \quad N = [\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_n]^T
\]

The time response series of MGM(1, \( n \)) model is:

\[
\hat{X}^{(1)}(k) = e^{\hat{M}(k-1)}X^{(1)}(1) + \hat{M}^{-1}\left(e^{\hat{M}(k-1)} - 1\right)\hat{N}, \quad k = 1, 2, \ldots
\]
Then, the restored value series is obtained by Eqn.(8).

\[
\begin{align*}
    \hat{X}^{(0)}(1) &= X^{(0)}(1), \\
    \hat{X}^{(0)}(k) &= \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1), k = 2, 3, \ldots.
\end{align*}
\] (9)

When \( n = 1 \), MGM\((1, n)\) is degenerated to GM\((1,1)\) model, and when \( M = 0 \), MGM\((1, n)\) model is degenerated to \( n \) GM\((1,1)\) models. The prediction steps of the MGM\((1,1)\) model are summarized as follows:

(1) selecting the running parameters of the system as status vector;
(2) establish MGM\((1, n)\) model and test the precision of the model;
(3) predict the developing tendency of the characteristics with the qualified model.

(4) update the unqualified model residual recognizing or data purifying, predicting repeatedly and so on.

As is shown in Figure 2, the characteristic parameters to be estimated feed into MGM\((1, n)\) model. The prediction sequences are put into AINN model to generate predicted value sequence. The raw data sequence \( \{ x_1^{(1)}(k), x_2^{(1)}(k), \ldots, x_n^{(1)}(k) \} \) \( (k = 1, 2, \ldots, m) \) from the status vector serve the input of the MGM\((1,n)\) model, which represent the running characteristics of the electromagnetic brake. Then the prediction sequence \( \{ \hat{x}_1^{(1)}(k), \hat{x}_2^{(1)}(k), \ldots, \hat{x}_n^{(1)}(k) \} \) feed into the AINN model to generate the expected prediction results.

4. Example for Fault Diagnosis

An example of fault prediction of electromagnetic brake is provided to verify the combined model consisting of AINN and grey MGM\((1, n)\) models. Selecting output voltage \( V \) and internal resistance \( R \) as the input parameters of the MGM\((1,n)\) to constitute MGM\((1,2)\) model. Then the predicted values \( \hat{V} \) and \( \hat{R} \) are fed into the AINN network after normalization processing. Extracting 100 data by stochastic means from the raw data sequence \( \{ v(k), r(k) \} \), then 50–100 data extracted from these data are fed into MGM\((1,2)\) model to get the forecasting value series \( \{ \hat{v}(k), \hat{r}(k) \} \). As is shown in Figure 3 that the actual values and predictive values are exactly similar. It implies that the proposed combined model is suitable to predict the characteristic values of the electromagnetic brake by MGM\((1,n)\) model.
kinds of typical samples are extracted to train the AINN network and are simulated by using the trained AINN model, showing better convergence with less average relative error, 0.068 only.

Table 1. Basic rules for fault prediction and diagnosis of electromagnetic brake.

| Characteristic parameters | Faults(8 kinds) |
|---------------------------|-----------------|
| V                         | R               |
| Undersize                 | 0.012 0.510     |
| Normal                    | 0.015 0.026     |
| Oversize                  | 0.012 0.01     |
| Undersize                 | 0.015 0.016     |
| Normal                    | 0.012 0.013     |
| Oversize                  | 0.012 0.013     |
| Undersize                 | 0.015 0.017     |
| Normal                    | 0.012 0.015     |
| Oversize                  | 0.012 0.015     |
| Undersize                 | 0.016 0.015     |
| Normal                    | 0.016 0.016     |
| Oversize                  | 0.016 0.016     |

The values of characteristic parameters $V$ and $R$ in different time are fed into AINN to generate predictive values with the results shown in Table 2. It implies from Table 2 that the combined model is practical for prediction value is very close to the diagnosis value.

Table 2. Prediction and decision results.

| Characteristic parameters | Prediction results | Decision results |
|---------------------------|--------------------|------------------|
| V                         | R                  |                  |
| 0.851                     | 0.852              | $F_1$            |
| 0.120                     | 0.112              | $F_2$            |
| 0.112                     | 0.852              | $F_2$            |
| 0.121                     | 0.458              | $F_4$            |
| 0.901                     | 0.120              | $F_5$            |
| 0.455                     | 0.893              | $F_6$            |

5. Conclusion
To find effectively the possible fault points of electromagnetic brake, a novel combined diagnosis model based on multivariable grey prediction model MGM(1,n) and adaptive integrated neural network (AINN) was proposed in this paper. The proposed mode has three main characteristics.

(1) For poor information and incomplete knowledge of the fault system, MGM (1, n) model gives an effective method to predict the development trend of multiple groups of fault feature factors.

(2) For the outputs of MGM (1, n) model, Fuzzy C-mean (FCM) algorithm can cluster the related influential factors of the faults points with effective manners.

(3) A case of electronic brake fault diagnosis is given, and the model analysis consisting of 8 possible faults is carried out, finding that the proposed combined model has better fault identification capacity with less error, showing stronger promotional practical value.

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