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# A load forecasting method of hard-shaft coupling multi-motor diving system[1]

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**Abstract.** A Learning Machine Extreme (ELM)-based load forecasting method was proposed against the nonlinearity, strong coupling and other issues in the load measurement of hard-shaft coupling multi-motor diving system. Signal preprocessing was conducted by selecting motor current and speed as auxiliary variables and via wavelet transform, ELM theory was adopted to set up a load forecast model of hard-shaft coupling multi-motor diving system. Experimental tests were carried out in the cutting part of thin seam shearer, the results show that the method is of high accuracy and the forecast error is less than 5%, which meets the requirement of field control.

**Key words.** Hard-shaft coupling, multi-motor, load forecast..

## 1. Foreword

Multi-motor dragging system has three coupling patterns—motor independence, flexible coupling and hard-shaft coupling. Multi-motor that adopts multi-motor drives the same device, which cannot only save space and improve power, but is also conducive to reduce rotary inertia of devices, shorten the transition process, reduce energy consumption, improve the system's dynamic performance and flexibility .

In hard-shaft coupling multi-motor dragging system, motor speed is in forced synchronization and output torque are inter-coupled, due to the differences in motor parameters, torque output must be controlled in order to improve efficiency [1-4].

In order to protect system security, current is usually selected as s control parameter. Therefore, this paper selects motor current and motor speed as the measurement parameters to conduct load forecasting of hard-shaft coupling multi-motor and to improve the basis for power balance control.

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## 2. Analysis of hard-shaft coupling multi-motor system

The hard-shaft coupling drive of the two three-phase induction motors in the cutting part of the thin seam shearer is taken as an example for analysis, and the hard-shaft coupling dual-motor system of the three-phase induction motors in the cutting part of the thin seam shearer are shown in Fig. 1 and are composed of two sets of three-phase induction motors, a transmission system, load, etc.

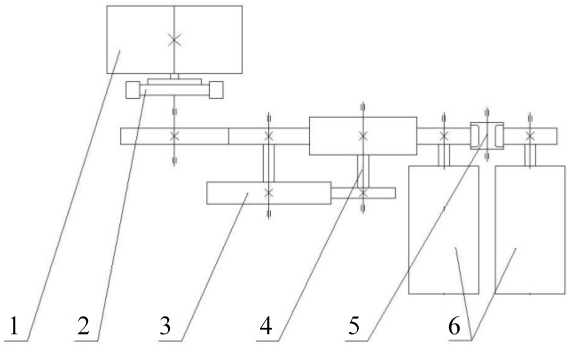


Fig. 1. Schematic diagram of hard-shaft coupling dual-motor transmission: 1–Load 2–Planetary gear train 3–Transmission gear 4–Elastic torque shaft 5–Idle gear 6–Motor

The dragging equation of the motor is:

$$T_{\mathrm{e}} - T_{\mathrm{f}} - T_{\mathrm{g}} = \frac{J_{\mathrm{p}}}{N_{\mathrm{p}}}\frac{\mathrm{d}\omega}{\mathrm{d}t}\,, \tag{1}$$

where $T_{\mathrm{e}}$ is the synthetic torque of motors M1 and M2, $T_{\mathrm{f}}$ is the resistance load torque, $T_{\mathrm{g}}$ is the drag load torque; $J_{\mathrm{p}}$ is the total rotary inertia of the system,, $\omega$ is the motor angular velocity, and $N_{\mathrm{p}}$ is the motor pole pairs.

According to the knowledge of motors, stator is static in $\alpha\beta$ coordinate system, and rotor rotates counterclockwisely in $\alpha'\beta'$ coordinate system with an angular velocity of $\omega$. According to the mathematical model of the induction motor, the torque equation reads

$$T_{\mathrm{g}} = N_{\mathrm{p}}(i_{s\beta}\psi_{s\alpha} - i_{s\alpha}\psi_{s\beta}) - \frac{J_{\mathrm{p}}}{N_{\mathrm{p}}}\frac{\mathrm{d}\omega}{\mathrm{d}t} - T_{\mathrm{f}}\,. \tag{2}$$

Here, symbols $i_{s\alpha}$ and $i_{s\beta}$ are the components of the stator current in coordinates $\alpha$ and $\beta$, while symbols $\psi_{s\alpha}$ and $\psi_{s\beta}$ denote the components of the stator flux linkage in the same coordinate system. Formula (2) reflects the relationship between load as well as stator current and speed of the motor. This relationship is obviously nonlinear.

In this paper, the stator current and speed of the motor are selected as auxiliary variables to forecast the output torque of multi-motor driving system and provide a basis for the rational allocation of power.

## 3. Load forecast modeling based on ELM theory

### *3.1. ELM theory*

Compared with traditional learning algorithms, Learning Machine Extreme (hereinafter referred to as ELM) has quick learning speed and good generalization performance, attracting more and more attention [5–10].

The feed forward neural network structure of a typical single hidden layer is shown in Fig. 2, the network has an input layer, a hidden layer and an output layer, wherein the input layer is fully connected to hidden layer and hidden layer is fully connected to output layer neurons.

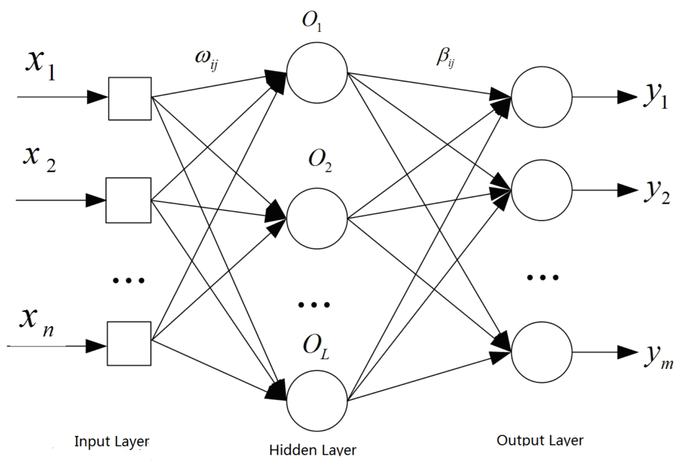


Fig. 2. Feed forward neural network structure of a typical single hidden layer

In this single hidden layer, the input layer of feedforward neural network has $n$ neurons, corresponding to $n$ input variables; hidden layer has $l$ neurons, output layer has $m$ neurons, corresponding to $m$ output variables and the connection weights between input layer and hidden layer as well as between hidden layer and output layer are $\boldsymbol{\omega}$ and $\boldsymbol{\beta}$, respectively. The threshold value of hidden layer neuron is $\boldsymbol{b}$, the training set with $Q$ samples has an input matrix $X$ and an output matrix $Y$, the activation function of hidden layer neuron is $g(x)$, the output of single hidden layer's feedforward neural network is $T$. Then the output of neural network can be denoted by

$$H\beta = T^{'}, \tag{3}$$

where, $T^{'}$ is the transposition of matrix $T$ and $H$ is the output matrix of hidden layer in the neural network.

It can be proved on the basis of previous studies that when activation function $g(x)$ is infinitely differentiable, the parameters of neural network need no adjustment, $\boldsymbol{\omega}$ and $\boldsymbol{b}$ can be randomly selected before the training, and remain unchanged in the training process, while the connection weight $\boldsymbol{\beta}$ between the hidden layer and output layer can be obtained by solving the set of equations

$$\min_{\beta} ||H\beta - T^{'}|| \,. \tag{4}$$

Its solution is

$$\hat{\beta} = H^{+}T^{'} \,, \tag{5}$$

where, $H^{'}$ is the Moore-Penrose generalized inverse of the output matrix $H$ in the hidden layer.

The main steps of ELM learning algorithm are as follows:

Step 1: Determine the number of neurons in hidden layer, set the connection weight $\boldsymbol{\omega}$ between input layer and hidden layer as well as bias $\boldsymbol{b}$ of neurons in hidden layer randomly.

Step 2: Select an infinitely differentiable function as the activation function of hidden layer neuron, and then calculate the output matrix $H$ of hidden layer.

Step 3: Calculate weight $\hat{\beta}$ of output layer: $\hat{\beta} = H^{+}T^{'}$.

It is, thus, clear that ELM is a very simple and quick learning algorithm. In order to ensure the convergence of algorithm, the number of hidden layer neurons in ELM network should be the same as the number of input learning samples.

### *3.2. Load forecast modeling*

Signal preprocessing shall be conducted first in an ELM measurement modeling process, on account of the strong noise reduction ability of wavelet transform, wavelet transform is thereby selected for signal preprocessing. ELM neural network has fast learning speed and high learning accuracy, therefore, this paper adopts a soft measurement modeling method that integrates wavelet transform and ELM neural network in conducting soft measurement of the cutting load of shearer. First, conduct wavelet transform of signals and modeling of the transformed signals using multiple ELM networks [5–7], then get the forecast output signal by taking the output of multiple ELM models as weighted mean. The soft measurement model structure that integrates wavelet transform and ELM network is shown in Fig. 3.

## 4. Experimental study

### *4.1. Testing experiment*

The principles of simulation experiment system of multi-motor driving system are shown in Fig. 3, which is mainly composed of the motor and its control circuit, loading device, connecting device, measuring device, etc.

During the experiment, continuous motor loading is achieved by adjusting the loading device. First, the operation data of single-motors are measured; then, the operation data of dual-motors are measured; finally, load measurement modeling is conducted using the experiment data. The experiment platform for design in this

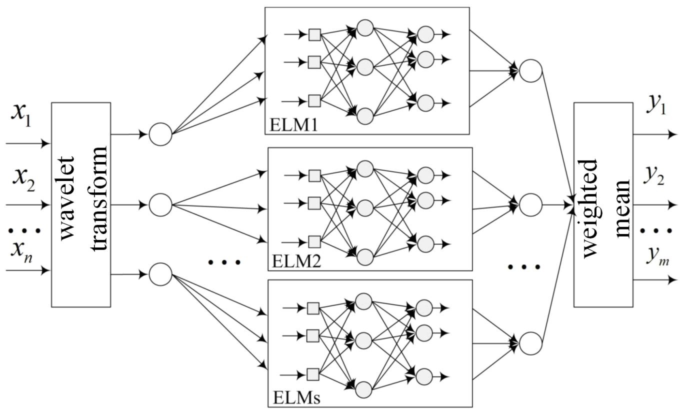


Fig. 3. Load measurement model integrating wavelet transform and ELM network

paper is shown in Fig. 4 and the experimental stand is depicted in Fig. 5.

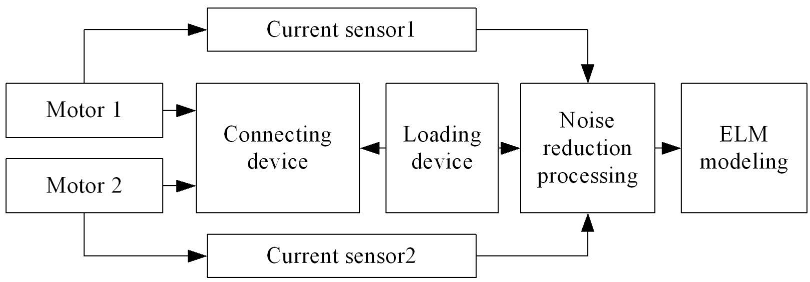


Fig. 4. Functional block diagram of multi-motor driving system and simulation experiment system

The experiment steps are as follows:

1. Keep motor speed unchanged, change motor load by adjusting the loading devices, and record the current value of motor stator.
2. Change motor speed and repeat step 1.
3. Repeat step 1 and 2 until getting enough data.
4. Divide the above data into test samples and training samples, train ELM network to get the load model of the motor.

### 4.2. Analysis of experiment results

The motor speed values in experiment process are, respectively, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0 times of the rated speed of the experiment, and the load is increased to 1.0 times from the rated 0.5 times at each speed.

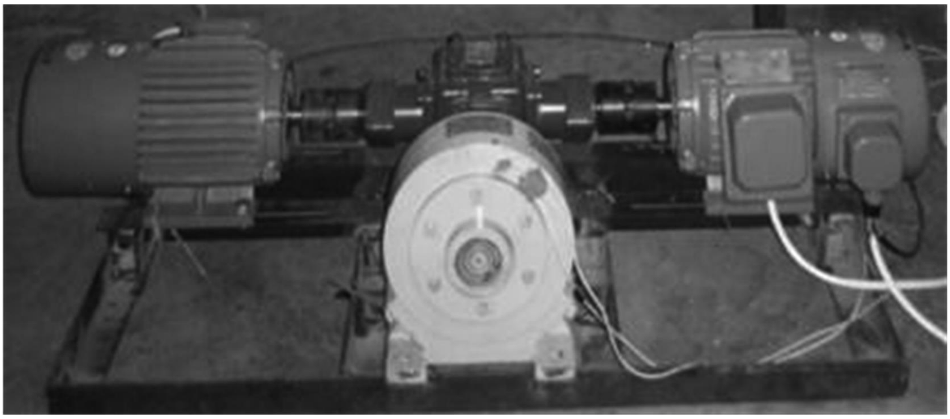

Fig. 5. Dual-motor driven simulation device

In the dual-motor driven experiment, 3 ELM models are used, modeling time is about 0.2 s. After several tests, one of the test results is shown in Fig. 6. We can see from the forecast results that the maximum error 0.02 A occurs at small load, the average value is adopted within the entire test range after 100 tests, and the average error is less than 5 %.

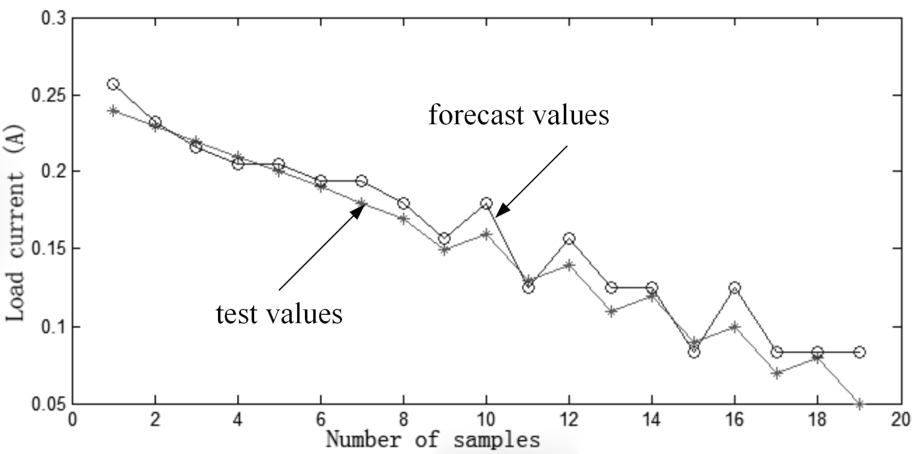


Fig. 6. The output result of dual-motor driven load forecast model

The above simulation results show that the forecast model set up by using ELM network has high measurement accuracy, the whole modeling process is 0.2 s, with high real-time capability, and the average forecast error is 5 %, which can be applied to engineering tests.

## 5. Conclusion

A load forecasting method that is based on wavelet transform and finite machine learning theory was proposed against the nonlinearity, strong coupling and other issues in the load measurement of current signal-based multi-motors, signal preprocessing was conducted by selecting motor current and speed as auxiliary variables and via wavelet transform, and a load measurement model was set up by using finite machine learning theory. Experiment data has proved the effectiveness of the method, modeling time is about 0.2 s and the load forecast error is less than 5 %, which can be achieved by online measurement.

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