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Fault Diagnosis Algorithm of Engine Cooling Fan Based on Physical Model and Support Vector Machine

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ABSTRACT

Engine electric accessories are a promising technical approach to improve engine fuel efficiency. The engine's electric cooling fan, however, with few signals to controllers, has a challenging fault detection issue. In this paper, a fault diagnosis algorithm based on model and support vector machine was proposed. Firstly, a dynamic model of electric motor-cooling fan system was established, then a real time model-based observer was designed to estimate the torque of the cooling fan. The load torque estimated with control signals was used to identify cooling fan model parameters. According to the identified parameters, a support vector machine (SVM) was utilized for fault classification . The simulation and experiment showed ,this diagnosis algorithm was able to discover over 98% mechanical failures with an classification accuracy of 95%.

Keywords: Electric fan, fault diagnosis, support vector machine.

1. INTRODUCTION

Engine is a highly coupled mechanical - electrical - thermal system, all control optimization is to achieve better energy management and conversion. Cooling system is the most important way of engine thermal management, cooling fan is the core component of the cooling system[1]. In normal work, the excess heat is taken away by converting electrical energy into kinetic energy, so as to promote the energy conversion efficiency, more heat energy is converted into mechanical energy. However, the fan will have stuck, blocked, bent and other faults. If it cannot be found in time, it will consume more electric energy, and even affect the normal operation of the engine in serious cases. Therefore, in order to achieve more efficient energy conversion, effective fault diagnosis is very necessary.

However, most cooling fan works in hash environment, and ECU can only judge whether the fan runs normally through extreme conditions such as over-pressure and over-current. Some faults cannot be detected or the cause of the fault cannot be correctly identified. As a result, the optimal maintenance time may be missed and system performance deteriorates. Therefore, in-time and effective fault diagnosis of cooling fan is of great significance for the reliability and economy of the vehicle in actual operation.

Physical model - based or data - driven methods are the main methods of cooling system fault diagnosis [2-4]. Nemati established corresponding models for different components, gave the judgment basis under fault conditions and designed the diagnostic algorithm, which achieved good diagnostic results[5]. Wu used the difference between the model and the actual water temperature to accurately diagnose the fault of the thermostat in the system[6]. However, in practice, the physical model-based diagnosis method often has a weak ability to identify different fault causes because of less monitoring variables.

A lot of scholars put much effort in data-driven diagnosis. Liet al. used Bayesian nonlinear estimation method for fault detection of chillers, which has good fault identification effect and good robustness[7]. Zhanet al. proposed a fuzzy SVM algorithm for refrigerator system, which can map data to high dimension by kernel function, and can effectively separate fuzzy information[8]. However, data-based diagnostic algorithms need a lot of data for training, and the real physical meaning of the data cannot be obtained through the model, which brings obstacles to further theoretical research.

To solve the problems above, a fault diagnosis method based on the combination of an electric fan physical model and support vector machine is proposed .With the physical model, the data demand for training is reduced and the fault identification degree

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under limited sample data was improved. The structure of the diagnosis algorithm is shown in Fig. 1

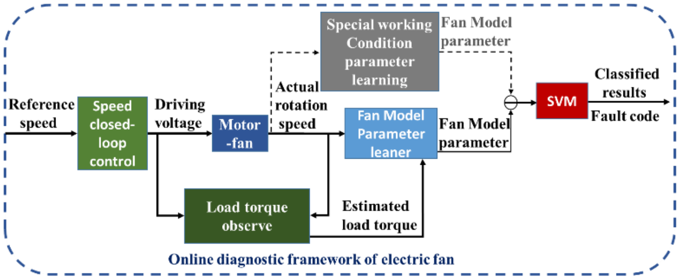

Fig.1 . Fault diagnosis algorithm structure

2 MODEL ESTABLISHMENT AND TRAINING

Based on the mathematical model of BLDC, the system dynamic model was established. The unknown parameters of the model were identified.

The equations of motion of BLDC and fan can be expressed as[9]:

$$Te - T_L - T_f = J\frac{dw}{dt} \quad (1)$$

$$T_f = Bw \quad (2)$$

In the formula, Te is Electromagnetic torque for motor, T_L is load torque, T_f is friction mandrel torque, J is moment of the inertia of the electric motor, w is motor speed,B is damping coefficient. Electromagnetic torque is the effective torque generated by the motor through electromagnetic force, and load torque is the torque of the motor to drive the fan.

2.1 Electromagnetic torque model

The electromagnetic torque equation of BLDC can be expressed as:

$$Te = \frac{ea*Ia + eb*Ib + ec*Ic}{w} \quad (3)$$

In the formula, Ia , Ib , Ic is three phase stator current(A); e_a , e_b , e_c is three-phase stator back electromotive force(V); w is motor speed (rad/s).

In this system, the BLDC stator winding is a three-phase star connection, and there is no midline extraction. The relationship between the voltage, current and back electromotive force of each phase winding is as follows[10]:

$$\begin{bmatrix} Ua \\ Ub \\ Uc \end{bmatrix} = \begin{bmatrix} Ra & 0 & 0 \\ 0 & Rb & 0 \\ 0 & 0 & Rc \end{bmatrix}\begin{bmatrix} Ia \\ Ib \\ Ic \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} * P\begin{bmatrix} Ia \\ Ib \\ Ic \end{bmatrix} + \begin{bmatrix} ea \\ eb \\ ec \end{bmatrix} \quad (4)$$

In the formula, Ua , Ub , Uc is three - phase stator voltage(V); Ia , Ib , Ic is three phase stator current(A); e_a , e_b , e_c is three-phase stator back electromotive force(V);L is self-inductance of three-phase stator winding(H);M is three-phase stator winding mutual inductance(H); Ra , Rb , Rc is Phase resistance of three-phase winding(Ω);P is differential operators.

Obtaining ideal back electromotive force waveform is one of the key issues in BLDC simulation modeling[11]. The back electromotive force modeling method adopted in this paper is the piecewise linear method [12-13]. This method is simple, feasible and has high accuracy, which can better meet the design requirements of modeling and simulation. As shown in Fig. 2, a running cycle of 0 - 360° is divided into six stages, each 60° is a reversing stage, and each running stage of each phase can be represented by a straight line. The back electromotive force waveform can be obtained by linear equation. Table (1) is the relationship between rotor position and back electromotive force, where k is the coefficient of back electromotive force, u is the electric angle signal (rad), w is the speed signal (rad/s). According to the electric angle of the motor, the back electromotive force is calculated and written by S-function.

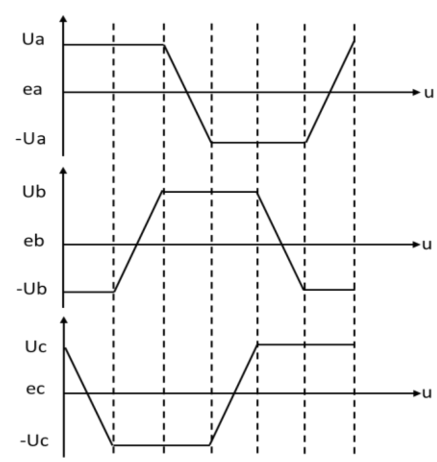

Fig.2 . Back emf waveform

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Tab. 1. Table of relationship between back electromotive force and rotor position

Rotor position	e_a	e_b	e_c
$0\sim\pi/3$	k*w	-k*w	k*w*((-u)/(π/6)+1)
$\pi/3\sim2\pi/3$	k*w	k*w*((u-π/3)/(π/6) -1)	-k*w
$2\pi/3\sim\pi$	k*w*((π/3-u)/(π/6)+1)	k*w	-k*w
$\pi\sim4\pi/3$	-k*w	k*w	k*w*((u-π)/(π/6)-1)
$4\pi/3\sim5\pi/3$	-k*w	k*w*((4π/3-u)/(π/6)+1)	k*w
$5\pi/3\sim2\pi$	k*w*((u-5π/3)/(π/6)-1)	-k*w	k*w

2.2 Fan model

Similar to that of a ship propulsion system driving a propeller, the motor-fan system can be expressed as[14] :

$$Qp = KQ * \rho * np^2 * D^2 \tag{5}$$

In the formula, K_Q is moment coefficient, n_p is propeller speed, D is slurry diameter, ρ is Seawater density. The fan model can refer to the propeller model, and the empirical model is as follows:

$$T_L = Aw^2 + C \tag{6}$$

Motor friction torque and driving fan load torque can be expressed as:

$$T_L + T_f = Aw^2 + Bw + C \tag{7}$$

A,B and C are model parameters to be calibrated. According to the data collected at different speeds, the nonlinear batch least square method is used to identify the offline parameters. The results are as follows :

Tab. 2. Parameter identification results of fan torque model

Parameter	Value
A	0.00000025
B	0.00024
C	0

2.3 Speed control module

The control module adopts PID algorithm. The input is the reference speed and the actual speed, and the output is the motor phase voltage. The Saturation limiter module limits the output three-phase voltage to the required range. Final Kp, KI, Kd adjusted to 1.2, 0.38, and 0.01.

2.4 Self-learning of model parameters

The fan model parameters can be learned by using the relationship between the rotational speed and the load torque and the friction torque in the shutdown process, and the model can be corrected by using each shutdown process [15]. (The shutdown speed is set at 3000 rpm.) The block diagram of the self-learning algorithm is as follows :

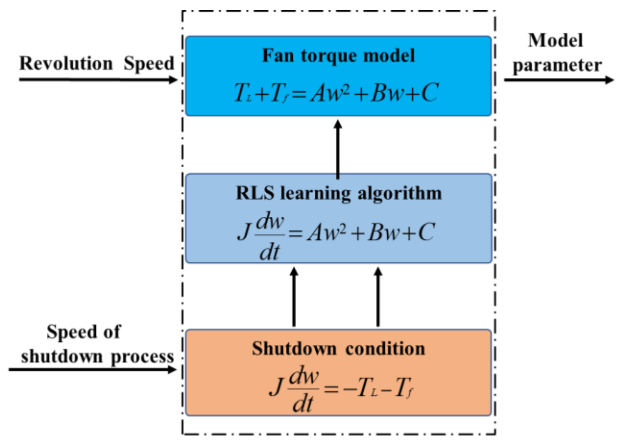

Fig.3 . Model parameter self-learning framework

3 FAULT DIAGNOSIS ALGORITHM DESIGN

3.1 Establishment of Load Torque Observer

In the process of motor rotation, the load torque is unknown and cannot be accurately calculated. Therefore, the load torque is equivalent to a part of the total external disturbance, which is observed by extended state observer(ESO) as the estimation value of the load torque[16].

Assuming a load change rate of 0, the expression to a model with load torque can be written as follows:

$$\begin{cases} \dfrac{dw}{dt} = \dfrac{Te - Tl - Tf}{J} \\ \dfrac{d(Tl)}{dt} = C \end{cases} \tag{8}$$

C is the assumed unknown constant. The load torque is unknown, and the fan model has estimation bias. In

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this paper, its influence is unified as the expansion state of 'total disturbance' .

$$\begin{cases} \dfrac{dw}{dt} = \dfrac{ea*Ia+eb*Ib+ec*Ic}{Jw} - \dfrac{Bw}{J} - f \\ \dfrac{d(f)}{dt} = C^{'} \end{cases} \tag{9}$$

f is total disturbance, $f = \dfrac{Tl+\varphi}{J}$, φ is Model deviation and unknown disturbance, $C^{'}$ is the assumed unknown constant.

Define a, b, g:

g=0,

$$b = \begin{cases} [\dfrac{kw}{RJw}, \dfrac{-kw}{RJw}, \dfrac{kw(-u/(\pi/6)+1)}{RJw}] & (0<u<\pi/3) \\ [\dfrac{w}{RJw}, \dfrac{kw((u-\pi/3)/(\pi/6)-1)}{RJw}, \dfrac{-kw}{RJw}] & (\pi/3<u<2\pi/3) \\ [\dfrac{kw((2\pi/3-u)/(\pi/6)+1)}{RJw}, \dfrac{kw}{RJw}, \dfrac{-kw}{RJw}] & (2\pi/3<u<\pi) \\ [\dfrac{-kw}{RJw}, \dfrac{kw}{RJw}, \dfrac{kw((u-\pi)/(\pi/6)-1)}{RJw}] & (\pi<u<4\pi/3) \\ [\dfrac{-kw}{RJw}, \dfrac{kw((4\pi/3-u)/(\pi/6)+1)}{RJw}, \dfrac{kw}{RJw}] & (4\pi/3<u<5\pi/3) \\ [\dfrac{kw((u-5\pi/3)/(\pi/6)-1)}{RJw}, \dfrac{-kw}{RJw}, \dfrac{kw}{RJw}] & (5\pi/3<u<2\pi) \end{cases}$$

$$a = \begin{cases} \dfrac{2k^2w^2+[kw(-u/(\pi/6)+1)]^2}{RJw} & (0<u<\pi/3) \\ \dfrac{2k^2w^2+[kw((u-\pi/3)/(\pi/6)-1)]^2}{RJw} & (\pi/3<u<2\pi/3) \\ \dfrac{2k^2w^2+[((2\pi/3-u)/(\pi/6)+1)]^2}{RJw} & (2\pi/3<u<\pi) \\ \dfrac{2k^2w^2+[kw((u-\pi)/(\pi/6)-1)]^2}{RJw} & (\pi<u<4\pi/3) \\ \dfrac{2k^2w^2+[kw((4\pi/3-u)/(\pi/6)+1)]^2}{RJw} & (4\pi/3<u<5\pi/3) \\ \dfrac{2k^2w^2+[kw((u-5\pi/3)/(\pi/6)-1)]^2}{RJw} & (5\pi/3<u<2\pi) \end{cases}$$

Convert the above (15) to the following :

$$\frac{dw}{dt} = bu + an + g + f \tag{10}$$

In the formula, u is power supply voltage input of controller. Since the rotational speed can be measured directly, an ESO observer for type (10) is designed. The formula (10) is deformed to obtain the expression of the total disturbance observation value.

$$f = \frac{dw}{dt} - bu - an - g \tag{11}$$

Then the load torque is obtained.

As shown in Fig. 4, Step test in the simulation platform, the load torque observer behaves well in estimation. When the step occurs, there is a maximum fluctuation of 2.5%. After stabilization, the estimation error is within 0.5 %.

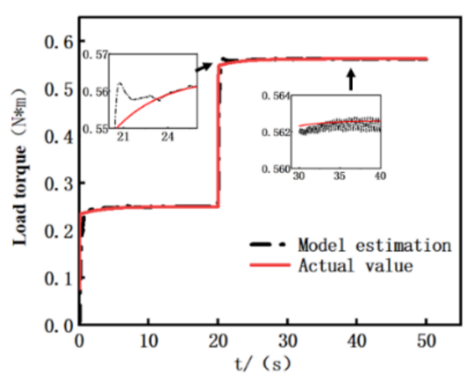

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Fig.4 . Comparison between estimated and theoretical values of upgrade test model.

3.2 Fault identification algorithm based on SVM

The load torque observer in section 3.1 can estimate the load torque in real-time, and the model coefficients of the fan model can be learned in real-time combined with the feedback speed. Under normal conditions, the model parameters are initial learning values. When faults occur, model parameters will fluctuate, and different faults will lead to different fluctuation ranges of model parameters. Therefore, the actual value of model parameters can be used to determine whether the fault exists and the category of this fault .

As the probability of the case that multiple faults occur simultaneously is relatively low[17], this paper only sets one fault at the same time(machine speed=0). The six-state parameters of the electronically controlled fan containing five typical faults are shown below.

Tab. 3. Parameter state under different faults

state number	state description	Parameter status
1	Fan stuck	A1
2	blade curving	A2
3	Leaf fall	A3
4	Fan obstruction	A4
5	normal	A5

The collected fault information is input into SVM-based fault identification algorithm to identify specific faults. The kernel function of support vector machine is the radial basis function, and the kernel penalty factor c and kernel function parameter q are 2 and 1 respectively.

Finally, five states listed in the above table were set, and 100 points in each state were taken as the total training set of SVM in the algorithm. To ensure the comprehensiveness of the training set, the training set contains fault data of different severity. Taking the fan blockage as an example, the rated output voltage should be increased by 10%, 20% and 30% respectively due to blockage. The execution rate of data acquisition training was 90%.

X represents the input of SVM, Y represents the output :

$$\begin{cases} X = \begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{bmatrix}^T \\ Y = \{\mathrm{State1},\ \cdots\cdots,\ \mathrm{State5}\} \end{cases} \tag{13}$$

4 VERIFICATION OF FAULT DIAGNOSIS ALGORITHM

For safety reasons, the faults of fan blocking, fan clamping, blade falling and blade bending were simulated on the simulation platform. The diagnosis algorithm can accurately identify these two faults.

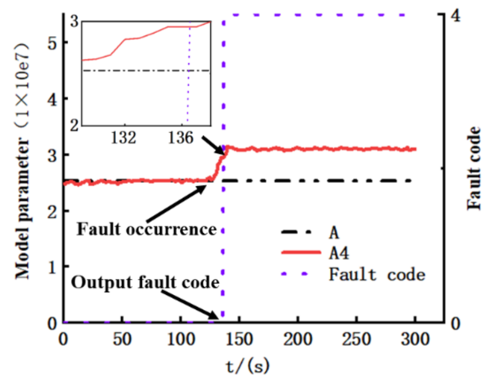

Fig.5 . Fan obstruction

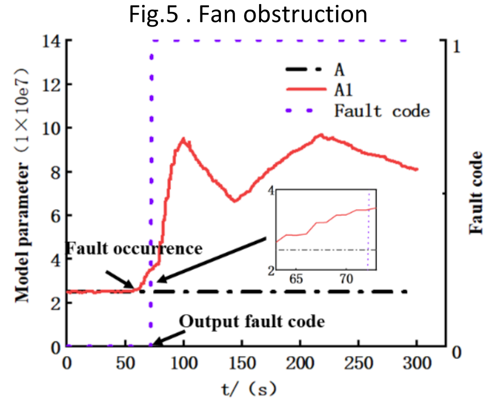

Fig.6 . Fan stuck

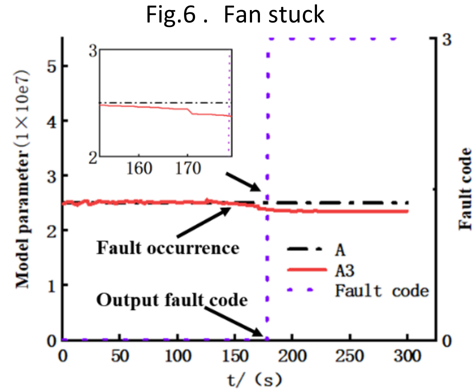

Fig.7 . Fan leaves fall

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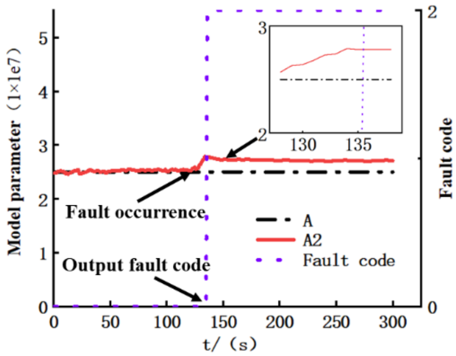

Fig.8 . Blade deformation

5 CONCLUSION

A fault diagnosis algorithm based on the combination of physical model and SVM was proposed. Through the load torque observer based on BLDC model, the fault information with high resolution is established under limited data. Then the fault information was used as the input of SVM fault classification and identification. Compared with model-based diagnosis, the classification accuracy is greatly improved, reaching more than 95%. The simulation results showed that the fault diagnosis algorithm can monitor the anomaly when the fault occurs, identify the cause of the fault quickly, improving energy conversion efficiency.

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