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PARAMETER ESTIMATION FOR ONLINE CONDITION MONITORING OF ROBOTIC MACHINES

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Abstract. *This paper proposes a novel learning approach to online condition monitoring of robotic machines. The real-time learning process comprises three stages, domain knowledge defining, random learning and ordinal learning. Domain knowledge defining abstracts the model of a robotic machine; random learning and ordinal learning stages train the parameters of the abstract model with random data selection and ordinal data selection, respectively. Simulation results have proved that the pro-posed method is efficient and feasible for online fault diagnosis of robotic machines.*

Key words: *Online machine learning, fault diagnosis and machine monitoring*

1. INTRODUCTION

In robotic machinery applications, brushless DC motors have been growingly dominant components because they are high accuracy and high power to size ratio, as well as easy to control. Besides, the fault diagnosis techniques have been moved in the past decade from traditional techniques to AI techniques. Such techniques do not require accurate models and fault analysis mechanism, but also provide promising solutions to challenging problems, e.g., incipient fault detection, for conventional techniques. However, the main drawback for AI techniques is that their heavy computation requirement. Almost all robotic machines require fault detection via online measurements. This paper proposes a neuron-learning based approach which targets the real-time fault diagnosis of robotic machines. This paper implements the proposed method into a specific DC brushless motor of our test-bed machine.

Fault diagnosis in robotic machines, especially those using induction motors has been intensively investigated in the past four decades [1]. This paper organizes relevant literature review in two categories: fault oriented and approach oriented. Motor fault-oriented research covers a wide variety of faults, e.g., motor rotor, mechanical load, motor bearing, broken bar, short circuits and incipient faults. For instance, Sobczyk et al [2] recognized rotor ecentricity based on Fourier spectra of phase currents; Cabanas et al [3] used experiments to detect rotor asymmetries; Thomson [4] diagnoses airgap eccentricity for detecting the fault of mechani-

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cal load using online current monitoring; Schoen & Habetler [5] uses stator current monitoring to diagnose motor bearing damage; Benbouzid et al [6] used a decentralized Neural Network to detect interturn short circuits and bearing wear. Incipient faults usually lead to motor failure by gradual deterioration of the motor if left undetected. For instance, Sottile & Kohler [7] proposed an online method to detect incipient failure of turn insulation in random wound motors. Furthermore, the listed faults are even difficult to diagnose if sensorless techniques are applied to the control systems of robotic machines. For instance, online motor diagnosis techniques proposed by Kim et al [8]. On the other hand, the approach-oriented category includes signal analysis based approaches, model-based approaches, AI/knowledge-based approaches and approaches combined the above-mentioned methods. Signal analysis based approaches do not need accurate models and are unsuitable for online diagnosis. Their characteristic methods are current analysis [5], spectra analysis [9] and signature analysis [10]. Model-based approaches require accurate models and suitable for real-time diagnosis, for instance, parameter estimation and state estimation [11]. Besides AI/knowledge-based approaches have shown their advantages in the fault diagnosis of robotic machines [12-17] because they can relax accurate models, could be applied to online computation, though they require necessary parameters. Additionally, there is a growing interest in combining the above-mentioned methods to fault diagnosis problems in recent years. It aims to integrate their advantages to achieve better diagnosis performance [14,15,17,18].

This paper is organized as follows: Section 2 presents the strategy for the online fault diagnosis; Section 3 introduces the model abstraction; Sections 4 and 5 propose Random Learners and Ordinal Learners. Finally this paper is highlighted with its technical contributions.

2. Online Learning Strategy

Online learning strategy for the fault diagnosis of robotic machines is organised in three stages: domain knowledge defining, random learning and ordinal learning, please see Figure 1. Domain knowledge defines the required domain knowledge from an abstract machine model. This is an important stage, as the machine model provides information of the diagnostic algorithm structure. The rest two stages refine and update the algorithm parameters with selected training data sets. Random learning inserts neurons to observe time independent data changes; ordinal learning inserts neurons to observe time dependent data changes. This two learning stages allow the proposed algorithm to adapt physical parameters of a robotic machine, e.g., a motor, to the provided abstract machine model. A threshold is defined by the experts in robotic machine, the threshold is used to measure whether the resultant algorithm is suitable to real-time diagnosis. If not, the configuration process re-starts from stage 1 to reallocate its Learners for the algorithm until the threshold is achieved. The re-configuration is caused by the domain knowledge defined at stage 1 is insufficient for the algorithm to realize for online diagnosis.

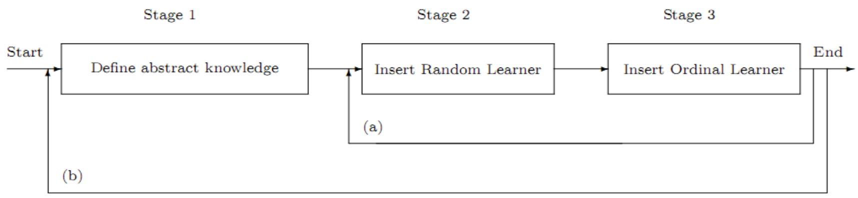

Fig. 1. the proposed online fault diagnosis flowchart

The core of the two learning stages is two types of Learners, i.e., a Random Learner and Ordinal Learner, which form the fundamental building blocks of a machine-learning model. The Learners aim to minimise losses by tuning weights W_n in a multiple-inputs-single-output linear function $y=\sum W_n*x_n$ as illustrated in Figure 2, but their learning natures are different. The Random Learner observes changes in data items $x_n \rightarrow y$, however, the Ordinal Learner observes the changes of data items against time $\{\{x_n,y\}_{j-1} \rightarrow \{x_n,y\}_j\}$. The structure of the Learners is based on the mathematical model of its monitored machine, as described in Section 3.

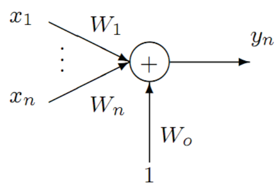

Fig. 2. Basic structure of a Learner, which is similar to a single neuron (Perceptron), consists of weights W and a summing ⊕ function.

For DC brushless motor-involved applications, fundamental modules are proposed in Figure 2, which are abstract structures of d-axis Learners and of q-axis Learners. Each consists of 2 Random Learners and 1 Ordinal Learner. The Random Learners estimate the inductance, number of poles and flux, whereas the Ordinal Learner estimates the resistance of the monitored motors.

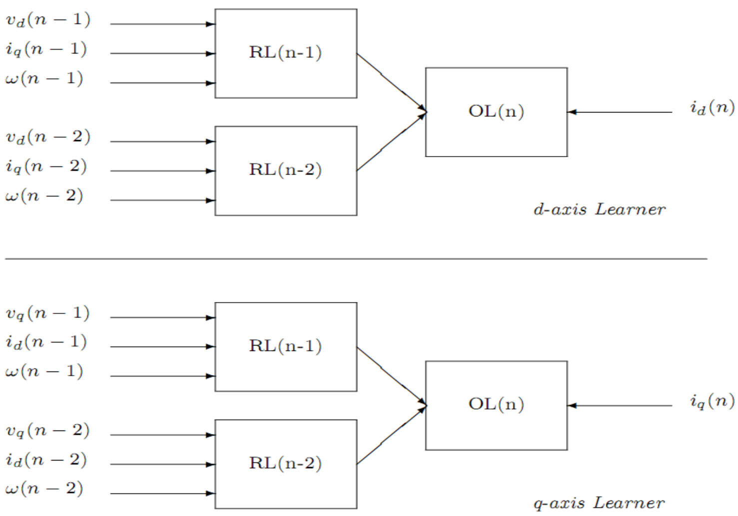

Fig. 3. An abstraction structure diagram of a d-axis Learner (top) and a q-axis Learner (bottom). RL represents a Random Learner and OL represents an Ordinal Learner.

3. Motor Model Abstraction

Generally speaking, artificial intelligent techniques, especially neural networks, generate the mapping from available inputs to expected outputs. In this case the proposed method works as a universal approximator to correlate relationships between the input demands and associated faults. For instance, supervising the training based on motor speed, current and some additional dynamics of the system, e.g., load torque [17] and 3-phases voltages [15]. This type of approximator has no prior knowledge about the system to be diagnosed.

Its goal is only to reduce the approximation error in mapping its inputs to a desired output. Additionally, to enhance the mapping performance of AI-based approaches, for instance, the artificial neural network, Fuzzy Logic [17, 14] and Wavelet analysis [15], it is unavoidable to introduces expensive computation for fault detection. Hence, a feasible algorithm for real-time fault diagnosis has to consider the tradeoffs between its efficiency and computational complexity.

The proposed approach is based on the use of domain knowledge which is an abstraction of a diagnosed robotic machine. The abstracted model provides fundamental parameters for the machine, it allows the learning algorithm to focus on refining the size and weights of the algorithm. That is to say, the abstracted model guides the learning processing to skip expensive training part and to adjust the algorithm weights in the suitable results regions. As a result, the abstracted model guides the algorithm to learn meaningful factors which are related to the physical parameters of monitor systems, on the other hand, it is likely that the complexity of the algorithm structure is close to that of a suitable model of a robotic machine due to the fact that the abstract model pre-configure the system structure.

This paper considers a robotic machine with a brushless DC motor. The machine's output torque T is proportional to its effective current I. The process of conversing from a 3-phase voltage V_{abc} to I can be divided into two parts represented by the Park-Clarke Transform and corresponding electrical subsystem [19-21]. The Park-Clarke Transform converts a 3-phase reference frame V_{abc} into a 2-phase orthogonal system V_{dq}. V_{abc} is also referred to as stationary frame and V_{dq} as rotating frame. The same transform can also be applied to V_{abc} to obtain V_{dq} by the following formula,

$$V_\alpha = \frac{2V_a}{3} - \frac{V_b}{3} - \frac{V_c}{3} \tag{1}$$

$$V_\beta = \frac{V_b - V_c}{\sqrt{3}} \tag{2}$$

$$V_o = \frac{V_a + V_b + V_c}{3} \tag{3}$$

and

$$V_d = V_\alpha \cos\theta - V_\beta \sin\theta \tag{4}$$

$$V_q = V_\alpha \sin\theta + V_\beta \cos\theta \tag{5}$$

The actual machine characteristic has been defined in terms of its model of electrical subsystem,

$$\frac{d}{dt}i_d = \frac{1}{L_d}V_d - \frac{R}{L_d}i_d + \frac{L_q}{L_d}pwi_q \tag{6}$$

$$\frac{d}{dt}i_q = \frac{1}{L_q}V_q - \frac{R}{L_q}i_q - \frac{L_d}{L_q}pwi_d - \frac{1}{L_q}\lambda pw \tag{7}$$

Where, i_d and i_q, V_d and V_q, L_d and L_q are current, voltage and inductance on d and q axes respectively. R, p and w are the winding resistance, number of pole pair and angular motor speed respectively.

For our test-bed machine, its Park-Clarke transform and abstract model have been implemented in MATLAB environment, see Figure 4 and Figure 5. The brushless DC motor model is driven by a standard drive model as illustrated in Figure 5, which consists of two control loops. The inner loop regulates the motor's stator currents and the outer loop controls the motor's speed.

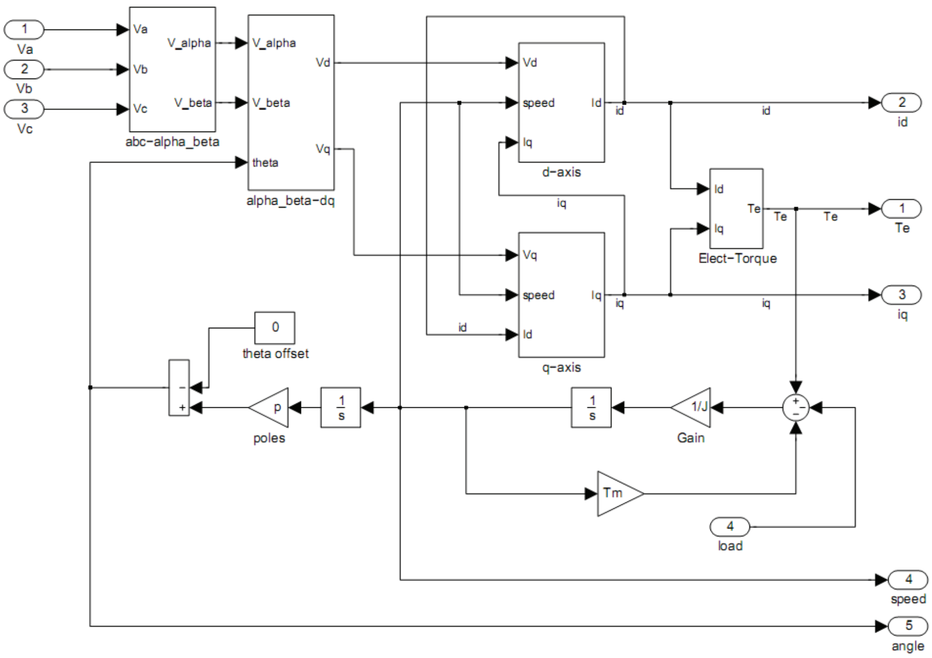

Fig. 4. Matlab Simulink model of an abstract brushless DC motor, which is represented by a Park-Clarke transform and a dc motor

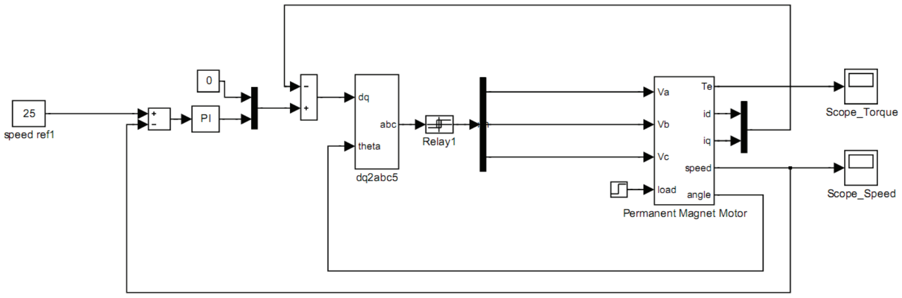

Fig. 5. Matlab Simulink model of a standard drive for brushless DC motor

4. RADOM LEARNERS

This section explores a fast operating Random Learner, with particular emphasis on its application to real-time online fault diagnosis. The proposed Learner uses an abstract mathematical model as its reference domain knowledge to configure a model structure. Experimental results show that, during training, the knowledge that the Learner has learnt is able to relate to the physical parameters of its monitoring model. The distinctive benefit of using the Learner is the monitoring of hidden system parameters which are difficult to obtain using physical sensors.

Learning is carried out by a gradient descending method. Error $E(W)$ is defined as the sum of partial errors $E(W)_k$ with regard to particular training patterns k. It also depends on the network weights W, and p is the total number of training patterns:

$$E(W) = \sum_{k=1}^{p} E_k(W) \tag{8}$$

The partial errors are defined as the sum of mean square error:

$$E_k(W) = \frac{1}{2}\sum_{t\in T}(y_j(W, x_t) - t)^2 \tag{9}$$

Where T is the target set. At a time n, the adaptation proceeds at discrete time steps that correspond to training epochs:

$$W_n = W_{n-1} + \Delta W_n \tag{10}$$

The learning process is the increment of the weights ΔW_n at time $n > 0$ that is proportional to the negative gradient of error function $E(W)$ at time $n - 1$:

$$\Delta W_n = -\frac{\delta E}{\delta W}(W_{n-1}) \tag{11}$$

4.1. Implement the Random Learner

The aim of this experiment is to test the feasibility of implementing the Random Learner and measure its performance. The simulation is carried out using Matlab Simulink on a Pentium III 800MHz PC. Training data is sampled every 0.1ms while a step demand is fed to the brushless DC motor abstract model to obtain its step response. A total of 301 samples are collected. The Learner model is configured to learn on the training data collected on i_d reference frame.

There are two modes of operation for the Random Learner: forward and learning. In forward mode, the Random Learner predicts i_d according to its trained weights W_w and W_o:

$$Y = Diag(\begin{bmatrix} W_{w1} & W_{o1} \\ W_{w2} & W_{o2} \end{bmatrix} \begin{bmatrix} V_d & W_d i_q \\ 1 & 1 \end{bmatrix}) \tag{12}$$

When the Random Learner learns, it calculates the error correction by:

$$e(n) = Y_d(n) - Y(n) \tag{13}$$

$$W_i(n+1) = W_i(n) + \alpha u_i(n) e(n) \tag{14}$$

The inputs to Random Learner are normalized after the learning via error back propagation is completed. A scaling factor S below is used to restore the actual trained weights of Learner.

$$S = (\frac{\max(Y_d)}{\max(V_d)}, \frac{\max(Y_d)}{\max(w_d i_q)}) \tag{15}$$

4.2. Experiment Results

The motor sample distribution (D) is divided into training sets and testing sets $(S_{train}, S_{Test}) \in D$. The Random Learner randomly selects 50 samples for its training set. Its training results after 5 epochs, 250 iterations are given in Figures 6 and 7. They have shown that the Random Learner estimated the hidden parameter W_{w1} to be $\approx$3068. The parameter W_{w1} relates to motor physical parameter L_d, i.e., $L_d \approx 0.326$. Besides, they have demonstrated that, after 3 epochs the training is converged. For each epoch, the Random Learner randomly selects 50 training samples. Random data selection has shortened the learning time from 218msec to 70msec.

In order to measure the convergence performance of a learning process, a convergence indicator W_o is introduced to monitor the learning processes. Ideally, the convergence indicator should be zero to indicate that the Random Learner finds the hidden parameter W_{w1}. Since W_o is fed by a constant value defined in equation 12 during training, $\delta W_o=0$ means the relevant error is not back-propagated, in other words, the learning process has been converged. This experiment has been repeated six times on both d-axis and q-axis using different datasets with added white noise, the results are summarised in Table 1. It indicates that the proposed method is also tolerant to noisy data, up to 20% added white noise has little effect on the diagnosis performance.

5. Ordinal Learners

An Ordinal Learner has been proposed to monitor finite time-dependent variables, it is trained with ordinary selected data. The idea behind this is to use the integration of randomly selected datasets and ordinary selected datasets to map the whole sample data space. Cascading Random Learners with Ordinal Learners allow us to further approximate higher ordered systems, and to explore the deep knowledge of a robotic system.

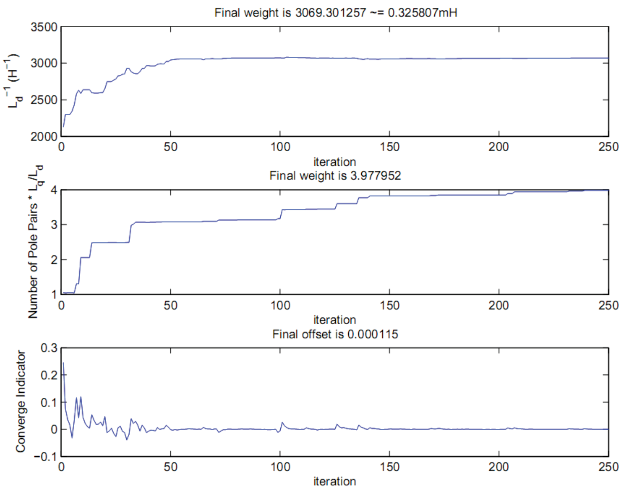

Fig. 6. Random Learner's knowledge of the monitored d-axis against time.

The estimated Ld (top) is ≈0.356mH and (middle) 4 poles. The Converge Indicator (bottom) shows that the Random Learner nearly converged after 150 interations.

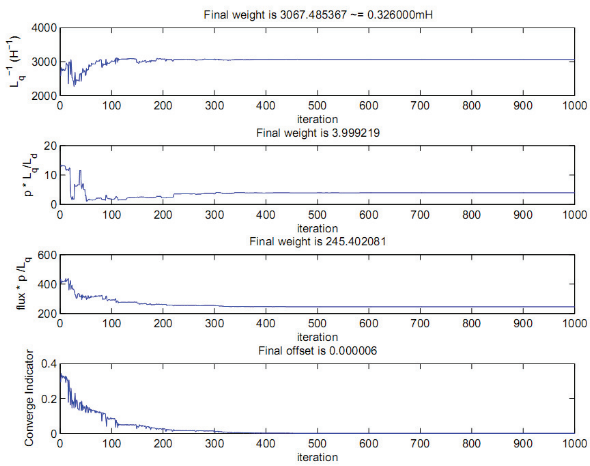

Fig. 7. Random Learner's knowledge of the monitored q-axis against time.

The estimated Lq (top) is ≈0.36mH, (2nd) 4 poles and (3th) flux ≈245.39*0.36m/4 = 0.02Wb. The Converge Indicator (bottom) shows that the Random Learner nearly converged after 300 iterations

For demonstration purpose, let's consider the following abstract model,

$$\frac{Y(s)}{X(s)} = G(s) = \frac{1}{s + R/L} \tag{16}$$

$$\frac{1}{s}x - \frac{R/L}{s}y = y \tag{17}$$

Using the backward difference rule, the discrete time derivate approximation is

$$y(kT_s) = \frac{dx}{dt}|_{t=kT_s} = \frac{1}{T_s}(x(kT_s) - x[(k-1)T_s]) \tag{18}$$

where T_s is the sampling time and k is a time pointer. And the its z-transform is obtained,

$$Y(z) = \frac{1-z^{-1}}{T_s}X(z) \tag{19}$$

Hence, the abstract approximation model of equation 17 becomes

$$\frac{T_s}{1-z^{-1}}x - \frac{T_s R/L}{1-z^{-1}}y = y \tag{20}$$

$$\frac{1}{R/L - T_s^{-1}}x + \frac{1}{1-T_s R/L}z^{-1}y = y \tag{21}$$

Table 1 Random learners' performance on d-axis and q-axis with datasets added white noise.

% white noise level	L_d mH	L_q mH	p_d	p_q	$flux * p_q/L_q$	$flux$ Wb
0 %	0.326	0.326	4	4	245.400	0.2
10 %	0.319	0.312	3.978	4.128	231.248	0.175
10 %	0.326	0.336	4.073	4.415	256.350	0.195
10 %	0.330	0.330	4.086	3.955	258.500	0.216
20 %	0.326	0.338	3.918	4.645	269.093	0.196
20 %	0.336	0.349	4.068	3.797	263.751	0.242
20 %	0.323	0.395	4.007	3.458	246.805	0.282

5.1. Experiment Results

Based on the Equation 21, the Ordinal Learners are trained by x and z^{-1} can estimate R of the test-bed machine. Implementing the Ordinal Learners into the proposed online fault diagnosis in Figure 8 and Figure 9 have shown simulation results of Ordinal Learners on both d-axis and q-axis. The selected dataset consists of 100 samples and is sampled at 0.1ms from our test-bed machine. Two datasets, x and $z^{-1}x$, are prepared to train the Learners, which the learning results are able to convert into physical parameter R.

The Converge indicators show both Learners converges after 500 iterations, which is 125ms in Matlab simulation with Windows 2000. Comparing with the model value *R=0.37,* the Ordinal Learners estimated *R={0.370,0.368,0.328,0.377},* therefore the maximum percentage error is 11%. One of the possible error source is due to the sampling error introduced from analog to digital signal conversion.

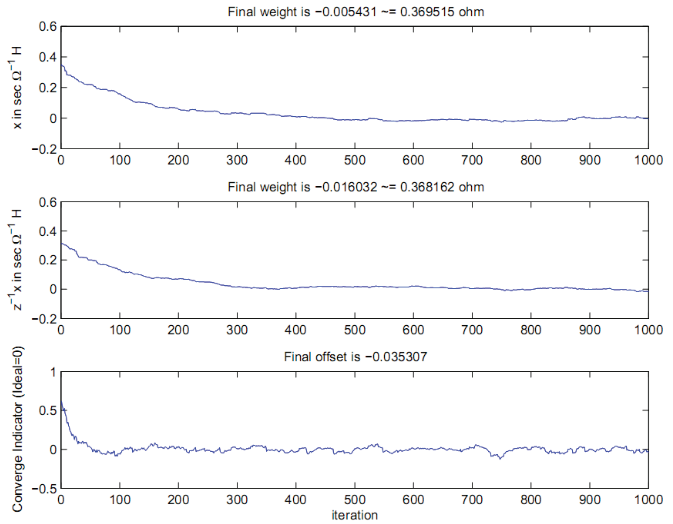

Fig. 8. Ordinal Learner's knowledge of the monitored d-axis against time. Approximation data is sampled at 0.1msec. (top) R estimated from x; (middle) R estimated from $z^{-1}x$; (bottom) Converge indicator.

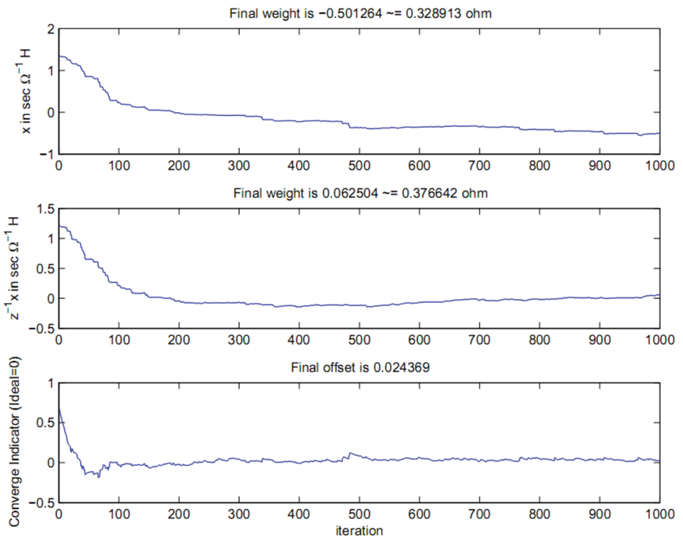

Fig. 9. The Ordinal Learner's knowledge of the monitored q-axis against time. Approximation data is sampled at 0.1msec. (top) R estimated from x; (middle) R estimated from z–1x; (bottom) Converge indicator.

6. CONCLUSION

This paper has proposed a framework for real-time fault diagnosis; it comprises domain knowledge defining, random learning and ordinal learning. The fundamental learning elements are two types of Learners: Random Learners and Ordinal Learners. The Random Learners estimate the inductance, number of poles and flux, whereas the Ordinal Learners estimate the resistance of the monitored motor.

Simulation and experimental results have shown that the proposed method has the freedom of self-adjusting weights with the guidance of domain knowledge of robotic machines. The method is also tolerant to noisy data, 20% of white noise has little effect on Learners' performance. The resultant weights of the algorithm are closely correlated to the physical parameters of the system.

REFERENCES

1. M.E.H. Benbouzid. Bibliography on induction motrs faults detection and diagnosis. IEEE Transactions on Energy Conversion, 14(4):1065–1074, 1999.
2. T.J. Sobczyk. Recognition of rotor eccentricity of induction motors based on the fourier spectra of phase currents. Proc. International Conference on Electrical Machines, 1:408–413, 1998.
3. M.F. Cabanas. Experimental application of axial leakage flux to the detection of rotor asymmetries, mechanical anomalies and interturn short circuits in working induction motors. Proc. International Conference on Electrical Machines, 1:408–413, 1998.
4. W.T. Thomson. A review of online condition monitoring techniques for induction motors-past, present and future. Proc. SDEMPED'99, pages 3–17, 1999.
5. R.R. Schoen and T.G. Habetler. Effects of time-varying loads on rotor fault detection in induction machines. IEEE Transactions on Industrial Applications, 31:900–906, 1995.
6. M.E.H. Benbouzid, M. Vierra, and C. Theys. Induction motors' faults detection and localization using stator current advanced signal processing techniques. IEEE Transactions on Power Electronics, 14(1):14–23, 1999.
7. J. Sottile and J.L. Kohler. An on-line method to detect incipient failure of turn insulation in random-wound motors. IEEE Transactions on Energy Conversion, 8(4):762–768, Dec 1993.
8. K. Kim, A.G. Parlos, and R.M. Bharadwaj. Sensorless fault diagnosis of induction motors. IEEE Transactions on Industrial Electronics, 50(5):1038–1051, 2003.
9. R.R. Schoen, B.K Lin, T.G. Habetler, J.H. Schlag, and S. Farag. An unsupervised, online systems for induction motor fault detection using stator current monitoring. IEEE Transactions on Industry Applications, 31(6):1280–1287, 1995.
10. P. Vas. Parameter estimation, condition monitoring and diagnosis of electrical machines. Oxford, UK: Clarendon, 1993.
11. K.R. Cho, J.H Lang, and S.D. Umans. Detection of broken rotor bars. IEEE Transactions on Engergy Conversion, 28:702–709, 1992.
12. F. Filippetti, G. Franceschini, C. Tassoni, and P. Vas. Recent developments of induction motor drives fault diagnosis using ai techniques. IEEE Transactions on Industrial Electronics, 47(5):994–1004, 2000.
13. M. Chow, R.N. Sharpe, and J.C. Hung. On the application and design of artificial neural networks for motor fault detection - part ii. IEEE Transactions on Industrial Electronics, 40, April 1993.
14. F.J. Uppal and R.J. Patton. Fault diagnosis of an electro-pneumatic valve actuator using neural networks with fuzzy capabilities. In ESANN'2002, pages 501–506, Belgium, April 2002.
15. K. Kim, A.G. Parlos, and G. Alexander. Induction motor fault diagnosis based on neuropredictors and wavelet signal processing. IEEE/ASME Transactions on Mechatronics, 7, June 2002.
16. X. Liu, H Zhang, J. Liu, and J. Yang. Fault detection and diagnosis of permanent-magnet dc motor based on parameter estimation and neural network. IEEE Transaction on Industrial Electronics, 47, Oct 2000.
17. S. Altug, M. Chow, and H.J. Trussell. Fuzzy inference systems implemented on neural architectures for motor fault detection and diagnosis. IEEE Transactions on Industrial Electronics, 46, Dec 1999.
18. H. Liu and G.M. Coghill. A model-based approach to robotic fault diagnosis. Knowledge-Based Systems, 18:225–233, 2004.
19. J. Solsona, M.I. Valla, and C. Muravchik. Nonlinear control of a permanent magnet synchronous motor with disturbance torque estimation. IEEE Transactions on Energy Conversion, 15, June 2000.

20. M. Fu and L. Xu. A novel sensorless control technique for permanent magnet synchronous motor (pmsm) using digital signal processor (dsp). In IEEE-PEDS'97, Singapore, May 1997.
21. D. Grenier, L.A. Dessaint, and O. Akhrif. Experimental nonlinear torque control of a permanent-magnet synchronous motor using saliency. IEEE Transactions on Industrial Electronics, 44, Oct 1997.

PROCENA PARAMETARA ONLAJN USLOVA MONITORINGA ROBOTSKIH MAŠINA

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Ovaj rad predlaže novi pristup u onlajn učenju uslova monitoringa robotskih mašina. Realno vreme procesa učenja sastoji se iz tri faze, domena odredjivanja znanja, slučajnog učenja i podregjenog učenja. Odredjivanje domena znanja sažima model robotske mašine; faze slučajnog učenja i podregjenog učenja utiču na parametre sažetog modela sa slučajno odabranim podacima i podregjenog odabranim podacima ponaosob. Rezultati simuliranja dokazuju da je predloženi metod efikasan iI izvodljiv za onlajn dijagnozu grešaka robotskih mašina.

Ključne reči: *Onlajn učenje, mašinsko učenje, dijagnoza grešaka, monitoring robotskih mašina*