On-load Parameter Identification of an Induction Motor Using Univariate Dynamic Encoding Algorithm for Searches

Jong-Wook Kim*, Nam Gun Kim**, Seong-Chul Choi**, and Sang Woo Kim**

* Technical Research Laboratories, POSCO, Pohang, Korea
(Tel : +82-54-220-6166; E-mail: kjune@posco.co.kr)
** Electrical and Computer Engineering Division , Pohang University of Science and Technology , Pohang, Korea
(Tel : +82-54-279-5018; E-mail: {kimng, alp, swkim}@postech.ac.kr)

Abstract: An induction motor is one of the most popular electrical apparatuses owing to its simple structure and robust construction. Parameter identification of the induction motor has long been researched either for a vector control technique or fault detection. Since vector control is a well-established technique for induction motor control, this paper concentrates on successive identification of physical parameters with on-load data for the purpose of condition monitoring and/or fault detection. For extracting six physical parameters from the on-load data in the framework of the induction motor state equation, unmeasured initial state values and profiles of load torque have to be estimated as well. However, the analytic optimization methods in general fail to estimate these auxiliary but significant parameters owing to the difficulty of obtaining their gradient information. In this paper, the univariate dynamic encoding algorithm for searches (uDEAS) newly developed is applied to the identification of whole unknown parameters in the mathematical equations of an induction motor with normal operating data. Profiles of identified parameters appear to be reasonable and therefore the proposed approach is available for fault diagnosis of induction motors by monitoring physical parameters.

Keywords: parameter identification, dynamic encoding algorithm for searches, induction motor, fault diagnosis

1. INTRODUCTION

The induction motor is one of the most popular electrical apparatuses owing to its simple structure and robust construction, and its power consumption ratio therefore occupies about 60% of domestic electric power demands. Specifically, for the uplift of productivity in continuous processes and reduction of downtime monitoring and/or fault diagnosis techniques for induction motors become more and more significant.

A number of diagnostic methods have been provided under the several categories of science and technology; electromagnetic field monitoring, temperature measurements, infrared recognition, noise and vibration monitoring, chemical analysis, and motor current signature analysis (MCSA), and so on [1]. The most relevant faults of induction motors are bearing faults, the stator or armature faults, the broken rotor bar and end ring faults, and the eccentricity related faults [1].

As is well known, MCSA is one of the most spread procedures to detect rotor faults. However a drawback of MCSA is the possible confusion with the motor current modulation produced by other events; pulsating load and particular rotor design. Owing to this difficulty, MCSA requires the user to have some degree of expertise in order to distinguish a normal operating condition from a potential failure mode [2].

This paper proposes a general-purpose diagnostic approach using physical parameters continuously estimated from voltage, current, and velocity data. The resistance and inductance values in an equivalent model are closely related with the status of an induction motor, while inertia and friction coefficient values indicate mechanical condition of bearings. Since these parameters themselves bear motor status information, no additional processing is required and even a motor operator can detect abnormality by observing parameter degradation or perturbation. Moreover, the estimated parameters can contribute to the vector control technique in which motor resistances and inductances are crucial.

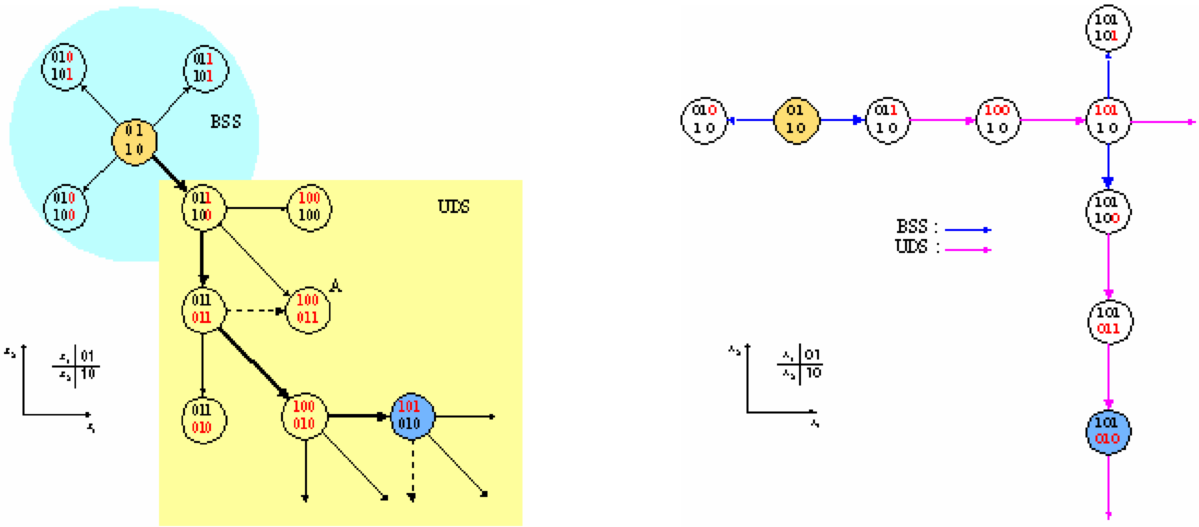
To extract the motor parameters during startup and on-load operation, continuous time system identification is preferred [3]. The numbers of total unknowns to be estimated amount from 6 (startup) up to 12 (on-load), and the 12 unknowns are hard to estimate by the conventional gradient-base methods. The genetic algorithm as an alternative consumes long execution time and shows in general poor performance for high dimensional problems.

DEAS had been developed from this need of a fast and robust optimization method for system identification since 2002. Despite its satisfactory results, the initial version of DEAS suffers from the exponential amount of function evaluation with the increase of problem dimension. To overcome this weakness, a variant of DEAS has been developed by concentrating only on the reduction of basic computation amount. The latter type is named univariate DEAS (uDEAS), while the former is classified as exhaustive DEAS (eDEAS). Despite much simpler search principles of uDEAS for the bisectional and unidirectional search schemes, benchmark result is quite promising even for low-dimensional test functions let alone high-dimensional functions. In this paper, the proposed optimization method, uDEAS, is employed to system identification of an induction motor by using input and output data perturbed by step-wise load change. We assume that changes in motor parameters will indicate relevant faults, and successful parameter identification result shows that the proposed diagnostic method is feasible and promising with convenience.

This paper is organized as follows. Section 2 describes uDEAS very briefly. Section 3 accounts for a system identification scheme of this paper. Section 4 provides a system identification result for on-load data of a normal induction motor. Section 5 concludes our work.

2. UNIVARIATE DEAS

The exhaustive dynamic encoding algorithm for searches (eDEAS) has been successfully applied to the parameter identification of an induction motor as shown in [4]. However, the exponential computation time of eDEAS became quite burdensome in searching for such 12 unknowns in a parameter vector. Since we aim at on-line parameter identification for monitoring induction motors search time is also an important



(a) BSS and UDS of eDEAS

(b) BSS and UDS of uDEAS

Fig. 1 Search aspects of BSS and UDS in both DEAS's

measure. Furthermore, a majority of significant systems contain unknown parameters ranging from tens to hundreds or more. Thus modification of eDEAS is inevitable for such problems.

An overall structure of uDEAS is basically identical with eDEAS in that the set of bisectional search (BSS) and unidirectional search (UDS) are iterated until a current row length of a solution matrix reaches a prescribed maximal length. However, a key difference of uDEAS is such that BSS is undertaken for one row, i.e. one parameter, not for every row as in eDEAS, and that the BSS-UDS set is carried out for each row like a building block.

Fig. 1 illustrates the difference of BSS and UDS in eDEAS and uDEAS. In eDEAS, BSS generates 2^n neighboring matrices (equivalently, real-valued vectors) by adding every possible column to a starting matrix. After evaluating their cost values and selecting the best matrix, UDS extends the promising direction by carrying out increment addition and decrement subtraction. Detailed description of BSS and UDS in eDEAS is well provided with pseudocodes in [3]. In Fig. 1(a), the thick line shows an optimal search path attained at each evaluation. The dashed line indicates that the corresponding movement will reach a matrix already visited by previous UDS. This revisit is readily protected by a simple masking technique [5]. Despite the evident success, eDEAS retains a fatal disadvantage of exponential evaluation.

Fig. 1(b) shows a modified search scheme of BSS and UDS in uDEAS developed for a mere reduction of computation amount. First, the two BSS neighbors (not matrices) along x_1 direction generated from an initial matrix of $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ are $\begin{bmatrix} 010 \\ 10 \end{bmatrix}$ and $\begin{bmatrix} 011 \\ 10 \end{bmatrix}$ unlike eDEAS. After evaluating and selecting a better one, UDS extends from it along the optimal direction (positive, in this case) as

$$\begin{bmatrix} 011 \\ 10 \end{bmatrix} \to \begin{bmatrix} 100 \\ 10 \end{bmatrix} \to \begin{bmatrix} 101 \\ 10 \end{bmatrix} \to \cdots.$$

Assuming the pseudo-matrix $\begin{bmatrix} 101 \\ 10 \end{bmatrix}$ is assessed as the best one, the above set of BSS and UDS is performed along x_2 direction, and a sound matrix $\begin{bmatrix} 101 \\ 010 \end{bmatrix}$ is attained after UDS in a similar manner. Fig. 1 shows that the final best matrices of eDEAS and uDEAS can be identical even through different search schemes of BSS and UDS. This situation is however restricted to a unimodal and smooth cost function.

Global optimization scheme of uDEAS is the same with that of eDEAS, i.e. the multistart approach. To check the search efficiency, uDEAS is benchmarked on the well-known test functions such as the Camel-back function, Rastrigin function, Schubert function, and so on [6], and function evaluation numbers of uDEAS are similar for two dimensional functions and much better for three and six dimensional functions compared with eDEAS, which is unexpectedly satisfactory despite the simple search schemes in BSS and UDS. The benchmark result is omitted in this paper for space limit.

3. IDENTIFICATION SCHEME

This paper addresses the model-based identification of motor parameters for motor status monitoring and/or fault diagnosis. The motor model described with nonlinear differential equation is acknowledged to be well suited to actual performance, which has led to an enormous success in vector control. Thus we assume that the model of induction motors is sufficiently precise for identification.

An induction motor can be described by the following differential equation in the *d-q* synchronous frame

$$\begin{aligned}
\dot{x}_1 &= a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + a_{14}x_4x_5 + b_1v_{ds} \\
\dot{x}_2 &= -a_{12}x_1 + a_{11}x_2 - a_{14}x_3x_5 + a_{13}x_4 + b_1v_{qs} \\
\dot{x}_3 &= a_{31}x_1 + a_{33}x_3 + a_{12}x_4 - x_4x_5 \\
\dot{x}_4 &= a_{31}x_2 - a_{12}x_3 + x_3x_5 + a_{33}x_4 \\
\dot{x}_5 &= a_{51}x_1x_4 - a_{51}x_2x_3 - a_{52}x_5 - a_{53}T_l
\end{aligned} \tag{1}$$

where

$$[x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5]^T = [i_{ds} \quad i_{qs} \quad \lambda_{dr} \quad \lambda_{qr} \quad \omega_r]^T$$

$$a_{11} = -\frac{1}{\sigma L_s}(R_s + \frac{L_m^2}{L_r T_r}), \quad a_{12} = \omega_e, \quad a_{13} = \frac{K}{T_r}, \quad a_{14} = K,$$

$$a_{31} = \frac{L_m}{T_r}, \quad a_{33} = -\frac{1}{T_r}, \quad a_{51} = -\frac{3P^2 L_m}{8JL_r},$$

$$a_{52} = \frac{B}{J}, \quad a_{53} = \frac{P}{2J}, \quad b_1 = \frac{1}{\sigma L_s},$$

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}, \quad K = \frac{L_m}{\sigma L_s L_r}, \quad T_r = \frac{L_r}{R_r}.$$

Among the above coefficients, R and L represent resistance and inductance, B and J denote friction coefficient and moment of inertia, and the subscripts s and r denote stator and rotor parts, respectively.

Genetic algorithm is capable of estimating whole physical parameters in Eq. (1) under startup condition [7][8]. Specifically at startup, owing to the zero initial condition and zero load torque, i.e. $T_l = 0$ in Eq. (1), all the unknowns are limited to a vector

$$\theta_1 = \left[R_s \ R_r \ L_s \ L_r \ L_m \ J \ B\right]. \tag{2}$$

Despite the small size of the parameter vector, the startup assumption is inappropriate for successive monitoring of an induction motor under on-load operation. Considering the null values at startup are no more zero under the on-load condition, the parameter vector to be estimated has to be lengthened as

$$\theta_2 = \left[R_s \ R_r \ L_s \ L_r \ L_m \ J \ B \ \lambda_{dr}(0) \ \lambda_{qr}(0)\right]. \tag{3}$$

In addition, the load torque T_l must also be estimated to integrate Eq. (1) by the Runge-Kutta formula. In view of system identification, it is more identifiable for input waveforms to contain a high persistent excitation condition. Noting in Eq. (1) that system input variables, v_{ds} and v_{qs}, are ideally almost constant after *d-q* transformation onto the synchronous frame, there exists as input only one term; external load torque T_l. The guideline in [9] suggests the external input T_l to be near a series of random numbers, which is not practical for on-load processes. Thus T_l is changed in a step-wise manner to raise system identifiability during experiments.

Fig. 2 illustrates an approximated load torque profile where T_l is divided into three phases as

$$T_l(t) = \begin{cases} T_{l1}, \quad t < t_{s1} \\ T_{l1} + \dfrac{\Delta T_l}{\Delta t}\left(t - t_{s1}\right), \quad t_{s1} \le t < t_{s1} + \Delta t \\ T_{l1} + \Delta T_l, \quad t_{s1} + \Delta t < t \end{cases} \tag{4}$$

where t_{s1} and T_{l1} represent the initial change time and the initial load torque, and Δt and ΔT_l denote the incremental time and incremental load torque, respectively.

In Eq. (4) ΔT_l is positive for increasing load torque and negative for decreasing load torque, while Δt is set always positive. Fortunately, magnitudes of three-phase stator currents are proportional to motor established torques, and detection of rms changes in stator currents therefore indicates a brief shape of T_l. Then the search parameter vector for on-load identification is augmented as

$$\theta_2 = \left[R_s \ R_r \ L_s \ L_r \ L_m \ J \ B \ \lambda_{dr}(0) \ \lambda_{qr}(0) \ t_{s1} \ \Delta t \ T_{l1} \ \Delta T_l\right]. \tag{5}$$

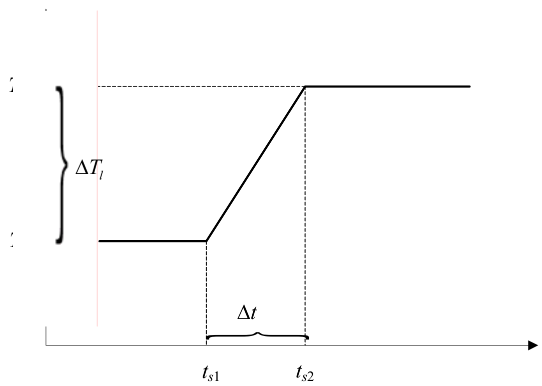


Fig. 2 An approximated profile of load torque

The cost function has to be carefully designed considering that the sensored data are of different order. In Eq. (1) i_{ds}, i_{qs} and ω_r are measured and compared with each evaluated value, i.e. $\hat{i}_{ds}, \hat{i}_{qs}$ and $\hat{\omega}_r$. Since all the unknowns in Eq. (1) are sought by uDEAS, the evaluated values can be attained at every instance of time. However, the absolute magnitudes of i_{ds}, i_{qs} vary from several tens to hundreds, while ω_r changes between 1750 and 1800 rpm. If these waveforms are normalized by their maximum absolute values, normalized ω_r will be suspended to unity with little perturbation. Therefore a mismatch of ω_r and $\hat{\omega}_r$ may not affect the prediction error cost which is conventionally a sum of normalized error between measured and evaluated data as

$$J_1 = \frac{T_s}{N}\sum_{k=1}^{N}\left\{\alpha\frac{\left|i_{ds}(t_k) - \hat{i}_{ds}(t_k)\right|}{\max\left|i_{ds}\right|} + \beta\frac{\left|i_{qs}(t_k) - \hat{i}_{qs}(t_k)\right|}{\max\left|i_{qs}\right|} + \gamma\frac{\left|\omega_r(t_k) - \hat{\omega}_r(t_k)\right|}{\max\left|\omega_r\right|}\right\}, t_k = t_0 + kT_s \tag{6}$$

where t_0, t_k, T_s, and N denote an initial measuring instant, the k-th instant, sampling time, and the number of samples, respectively. The coefficients $\alpha, \beta,$ and γ are adopted for enhancing the terms of interest or relatively small. However, balancing the three terms in Eq. (6) with the coefficients is another troublesome task.

To overcome such difficulties in the multi-objective optimization, this paper proposes a new normalization technique of cost function as

$$J_2 = \frac{T_s}{N}\sum_{k=1}^{N}\left\{\left|\tilde{i}_{ds}(t_k) - \tilde{\hat{i}}_{ds}(t_k)\right| + \left|\tilde{i}_{qs}(t_k) - \tilde{\hat{i}}_{qs}(t_k)\right| + \left|\tilde{i}_{ds}(t_k) - \tilde{\hat{i}}_{ds}(t_k)\right|\right\}, t_k = t_0 + kT_s \tag{7}$$

where

$$\tilde{x}(i) = \frac{x(i) - \min x}{\max x - \min x}. \tag{8}$$

The normalizing function of Eq. (8) maps a series of arbitrary numbers into the values between 0 and 1. Thus irrespective of variations and magnitude orders in sensored data all the waveforms are squeezed into the normal range. Moreover, no weighting coefficients are required in Eq. (7)

owing to the normalizing function.

Experimental tests are carried out on a 30kW four-pole three phase induction motor connected directly to 440V line-to-line voltage sources. For measuring and saving voltage and current signals into a PC, a data acquisition system with A/D converters, WaveBook516A of IOTECH, and three current probes of CHAUVIN ARNOUX whose measuring scope is 1 to 1000A are used. Since the permissible range of the acquisition system is -2.5 to 2.5V, line-to-line voltage signals are shunted and lowered by power transformers for measurement. Three stator currents are acquired by the Hall transducers and transformed to voltage signals by a resistor prior to the acquisition system whose sampling time is set 10kHz.

The raw input and output signals contain quantization and measurement noises. Since output signals are evaluated from measured input signals, the unfiltered noises, consequently, affect the values of identified parameter. A linear phase FIR filter, which is symmetric and type 1, is employed for this purpose [10]. The bandwidth and the filter order are set 50Hz and 101, respectively.

4. SYSTEM IDENTIFICATION RESULT

Parameter identification is carried out at two phases; start up and normal operation. At startup, the parameter vector is set as Eq. (2) and search range of each parameter is specified as

- $R_s, R_r : 0.01 \sim 5\Omega$
- $L_{ls}, L_{lr} : 0.01 \sim 10mH, L_m : 1 \sim 100mH$
- $B_r : 0.0001 \sim 1, J : 0.001 \sim 10$.

Note that leakage inductances are estimated rather than stator and rotor inductances because of system stability. That is, since a negative leakage factor σ attained during search makes the system of Eq. (1) unstable, there has to be a restriction of $L_{s,r} > L_m$, which is always satisfied by the above search range of leakage inductances.

Search parameters of uDEAS are configured as

- optInitRowLen = 3
- maxRowLen = 15
- numMaxRestart = 50
- parame dimension = 7 (no load), 13 (on-load).

The above specification implies that multistart is undertaken 50 times from random binary matrices of row length 3 and each trial is stopped when matrix row length reaches maximum row length of 15. Then the best-so-far parameter attained during the search with uDEAS is considered as a global minimum.

Fig. 3 shows that the output waveforms simulated with the best parameters sought by uDEAS match well with the measured waveforms. The deviations at a rising time occur owing to distortion of phase currents which is typical to the direct-on-line start. Nevertheless the established torque profile shown at the bottom of Fig. 3 makes sense, and its constant offset attributes to the frictional force.

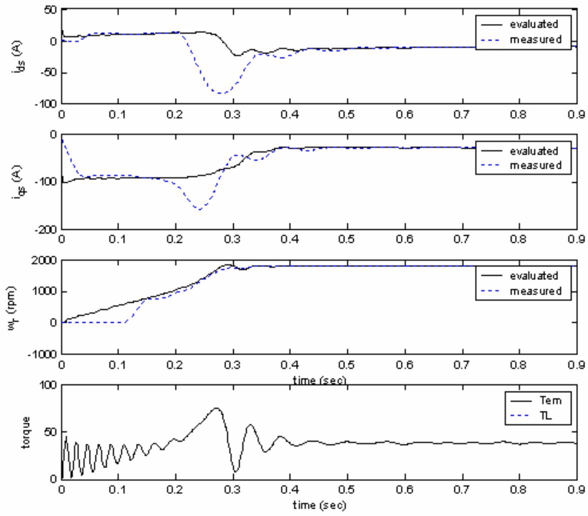


Fig. 3 Comparison of measured and evaluated signals for no-load startup

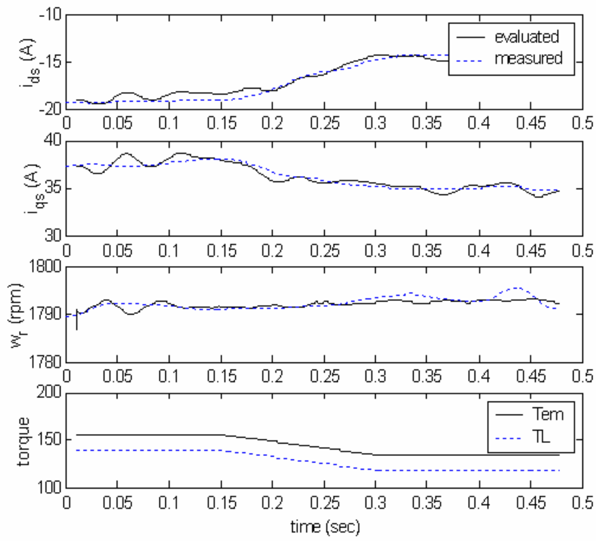


Fig. 4 Comparison of measured and evaluated data for on-load operation

At normal operation, the number of parameter increases up to 12. It is often an important and difficult task in resolving optimization problems to determine each parameter bound. If the bounds are set too wide or partially inclusive of global optimum, optimization will be in general inefficient. Fortunately, the continuous-time system identification has the advantage that each model parameter retains physical meaning. Moreover, the electrical elements such as resistors and inductors in the equivalent model vary slowly with temperatures. Therefore the formerly estimated values provide uDEAS with good guess of optimal bounds of next values like the following

- $R_s, R_r, L_m : 10 \sim 200\%$ of former values.

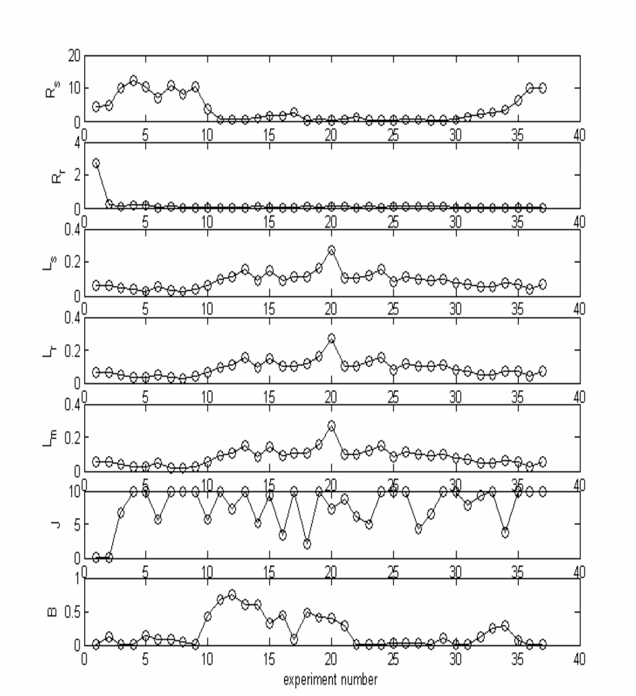


Fig. 5 Profiles of continuously estimated motor parameters for on-load operation

The other motor parameter bounds are enclosed irrespective of formerly estimated values as

- $L_{ls}, L_{lr} : 0.01 \sim 10mH$
- $B_r : 0.0001 \sim 1, J : 0.001 \sim 10$
- $\lambda_{dr}(0), \lambda_{qr}(0) : -2 \sim 2$.

The two time parameters concerning load change are sought near the approximated values computed by phase currents as

- $t_{s1},\ \Delta t : 70 \sim 130\%$ of measurement

The two load torque related parameters have to be searched in a similar fashion with reference to the previously estimated values. However, since load torque changes in a wide region, the percentage boundaries are somewhat absurd. Thus absolute values are used for bounds as

- T_{l1} : -30~30 of the previous T_{l2}
- $\Delta T_l : \begin{cases} -50 \sim -5 \text{ for decreasing load} \\ 5 \sim 50 \text{ for increasing load} \end{cases}$.

Fig. 4 shows that the computed output signals using a best parameter vector of Eq. (5) are well suited to measured signals. Fig. 5 provides the profile of parameters estimated by uDEAS within the dynamic bounds described above. Load torque was gradually increased until experiment number 20 and decreased to zero afterwards. Under exertion of low load torque to the induction motor stator resistance appear to be high, while rotor resistance is almost constant. However, inductance values change in proportion to load torque values, which is reasonable. The inertia and frictional coefficient values however perturb owing to small changes in rotor velocities, i.e. low PE condition. This weakness can be overcome by controlling rotor velocities with inverters.

5. CONCLUSION

This paper proposes an improved version of DEAS, i.e. uDEAS, and applied it to the parameter identification of an induction motor. To raise an applicability of the proposed identification approach, input and output signals of the motor are measured during load changes manually exerted. The identification result is promising with small search time (a few minutes in estimating 12 unknowns).

To apply this method to monitoring and/or fault diagnosis of induction motors temperature compensation has to be carried out to estimation of resistance values, and rotor velocity has to be widely changed using inverters.

REFERENCES

[1] S. Nandi and H. A. Toliyat, "Condtion monitoring and fault diagnosis of electrical machines – a review," *Proc of the 34th IAS Annual Meeting*, Vol. 1, pp. 197-204, 1999.

[2] M. E. H. Benbouzid, "A review of induction motors signature analysis as a medium for faults detection," *IEEE. Trans. Industrial Electronics*, Vol. 47, No. 5, pp. 984-993, 2000.

[3] J. –W. Kim and S. W. Kim, "A novel parametric identifi cation method using a dynamic encoding algorithm for s earches (DEAS)," *International Conference on Control, Automation, and Systems*, pp. 406-411, 2002.

[4] J. –W. Kim, S. J. Kim, and S. W. Kim, "Parameter identi fication of induction motors using dynamic encoding al gorithm for searches (DEAS)," *IECON*, pp. 150-155, 20 03.

[5] J. –W. Kim and S. W. Kim, "Gain tuning of PID controll ers with the dynamic encoding algorithm for searches (DEAS) based on the constrained optimization technique ," *International Conference on Control, Automation, an d Systems*, pp. 871-876, 2003.

[6] A. Törn and A. Zilinskas, Global Optimization, Springer -Verlag & Berlin, 1989.

[7] F. Alonge, F. D'lppolito, G. Ferrante, and F. M. Raimond i, "Parameter identification of induction motor model us ing genetic algorithms," *Proc. Inst. Elect. Eng. Contr. T heory Applicat.*, Vol. 145, No. 6, pp. 587-593, Nov. 199 8.

[8] K. S. Huang, Q. H. Wu, and D. R. Turner, "Effective identification of induction motor parameters based on fewer measurements," *IEEE Trans. Energy Conversion*, Vol. 17, No. 1, pp. 55-60, March 2002.

[9] L. Ljung, *System Identification : Theory for the user*, Englewood Cliffs, NJ:Prentice-Hall, 1987.

[10] S. Salous, "The design of linear phase FIR filters using the IDFT,"' *IEEE Trans. Education*, vol. 41, no. 3, pp. 229-231, August 1998.