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Optimization of Adaptation Gains of Full-order Flux Observer in Sensorless Induction Motor Drives Using Genetic Algorithm

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Abstract: This study presents a new optimization method of the adaptation PI gains of the full-order flux observer in the sensorless induction motor drives. The new method employs a Genetic Algorithm (GA) based optimization routine that can be implemented off-line. A suitable fitness function is defined to assess the tracking performance, the noise sensitivity and the stability of the rotor speed estimation system when each individual's parameters are employed. The tournament selection is used to choose the parent individuals and a large mutation probability is used to prevent the evolution from the prematurity. The PI gains calculated according to the design guidelines are put in the initial population to quicken the optimization procedure. With the help of the proposed method, the desirable PI gains can be obtained and the optimization procedure is fast and efficient. Simulation results show that the estimated speed tracks the practical speed well when the obtained PI gains are employed. Simulation results validate the proposed method in the study. Since, the efficient optimization ability, the Genetic Algorithm (GA) is pretty suitable for the optimization of the adaptation PI gains of the full-order flux observer in the sensorless induction motor drives.

Key words: Genetic algorithms, sensorless, adaptive full-order flux observer, induction motor drives

INTRODUCTION

The speed-adaptive full-order observers are promising flux estimators for the sensorless induction motor drives (Yang and Chin, 1993; Hofmann and Sanders, 1998; Holtz and Quan, 2002; Maes and Melkebeek, 2000; Kubota *et al*., 2002; Lascu *et al*., 2006; Ohyama *et al*., 2006). The speed-adaptive observer consists of a state-variable observer and a rotor speed adaptation mechanism. The characteristic of the estimation is governed by the assignation of the state-variable observer's feedback gains and the adaptation Proportional-Integral (PI) gains.

The assignation of the feedback gains has received lots of attention while the adaptation gains received a little in the past research studies. The determination of the adaptation gains can be time consuming as it is usually done by trial and error (Kubota *et al*., 1993). It is concluded that except for sensitivity to noises, fast tracking performance can be achieved by using as large adaptation gains as possible (Peng and Fukao, 1994; Schauder, 1992). It is revealed that a good tracking performance of the speed estimator during acceleration/deceleration can be achieved with a high integral adaptation gain while the sensitivity to current measurement noises can be reduced by designing a low proportional adaptation gain (Suwankawin and Sangwongwanich, 2006). It is also pointed out that a suitable corner frequency of the adaptation PI gains is required to avoid an oscillation. Suwankawin and Sangwongwanich (2002) presented design guidelines of the adaptation PI gains for the speed estimator. However, it is not easy to make a trade off to calculate the desirable adaptation PI gains which guarantee all good performances.

This study presents a new method to optimize the adaptation PI gains using Genetic Algorithm (GA) in order to obtain the good performances of the rotor speed estimation system, which include the accurate tracking performance, the low noise sensitivity and the efficient stability. With the proposed method in this study, the optimization procedure is fast and efficient. Simulations are carried out to validate the efficiency of the proposed method.

ROTOR SPEED ESTIMATION WITH ADAPTIVE FULL-ORDER OBSERVER

Induction motor model: For the induction motor, the dynamic model viewed from the stator reference frame (α-β frame) can be expressed as follows:

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$$p\cdot\begin{bmatrix}\vec{i}_s\\ \vec{\psi}_r\end{bmatrix}=\begin{bmatrix}A_{11} & A_{12}\\ A_{21} & A_{22}\end{bmatrix}\begin{bmatrix}\vec{i}_s\\ \vec{\psi}_r\end{bmatrix}+\begin{bmatrix}B_1\\ 0\end{bmatrix}\vec{v}_s \tag{1}$$

Where:

$$\vec{i}_s=\begin{bmatrix}i_{s\alpha}\\ i_{s\beta}\end{bmatrix},\ \vec{\psi}_r=\begin{bmatrix}\psi_{r\alpha}\\ \psi_{r\beta}\end{bmatrix},\ \vec{v}_s=\begin{bmatrix}v_{s\alpha}\\ v_{s\beta}\end{bmatrix}$$

$$A_{11}=-\{R_s/(\sigma L_s)+(1-\sigma)/(\sigma\tau_r)\}I$$

$$A_{12}=L_m/(\sigma L_s L_r)\{(1/\tau_r)I-\omega_r J\}$$

$$A_{21}=(L_m/\tau_r)I$$

$$A_{22}=-(1/\tau_r)I+\omega_r J$$

$$B_1=1/(\sigma L_s)I$$

$$\tau_r=\frac{L_r}{R_r}\qquad \sigma=1-\frac{L_m^2}{L_s L_r}$$

$$I=\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}\qquad J=\begin{bmatrix}0 & -1\\ 1 & 0\end{bmatrix}\qquad p\cdot=\frac{d}{dt}$$

where, $\vec{i}_s$ is the stator current vector, $\vec{\psi}_r$ is the rotor flux vector, $\vec{v}_s$ is the stator voltage vector, R_s is the stator resistance, R_r is the rotor resistance, L_s is the stator self-inductance, L_r is the rotor self-inductance, L_m is the mutual inductance and ω_r is the rotor electrical speed.

Speed-adaptive full-order flux observer: From the model Eq. 1, we can build a full-order observer as shown in Eq. 2-3:

$$p\cdot\begin{bmatrix}\hat{\vec{i}}_s\\ \hat{\vec{\psi}}_r\end{bmatrix}=\begin{bmatrix}A_{11} & \hat{A}_{12}\\ A_{21} & \hat{A}_{22}\end{bmatrix}\begin{bmatrix}\hat{\vec{i}}_s\\ \hat{\vec{\psi}}_r\end{bmatrix}+\begin{bmatrix}B_1\\ 0\end{bmatrix}\vec{v}_s+G(\hat{\vec{i}}_s-\vec{i}_s) \tag{2}$$

$$\begin{aligned}\hat{\omega}_r&=\left(K_P+K_I\int dt\right)\hat{\vec{\psi}}_r^{T}J\vec{\varepsilon}_i\\ &=\left(K_P+K_I\int dt\right)\left(\varepsilon_{i\alpha}\hat{\psi}_{r\beta}-\varepsilon_{i\beta}\hat{\psi}_{r\alpha}\right)\end{aligned} \tag{3}$$

Where:

$$\hat{A}_{12}=L_m/(\sigma L_s L_r)\{(1/\tau_r)I-\hat{\omega}_r J\}$$

$$\hat{A}_{22}=-(1/\tau_r)I+\hat{\omega}_r J$$

$$\vec{\varepsilon}_i=\vec{i}_s-\hat{\vec{i}}_s=\begin{bmatrix}\varepsilon_{i\alpha} & \varepsilon_{i\beta}\end{bmatrix}^T$$

where, G is the feedback gain matrix of the full-order observer, ∧ denotes the estimated variables, K_P, K_I are PI gains of rotor speed adaptive mechanism.

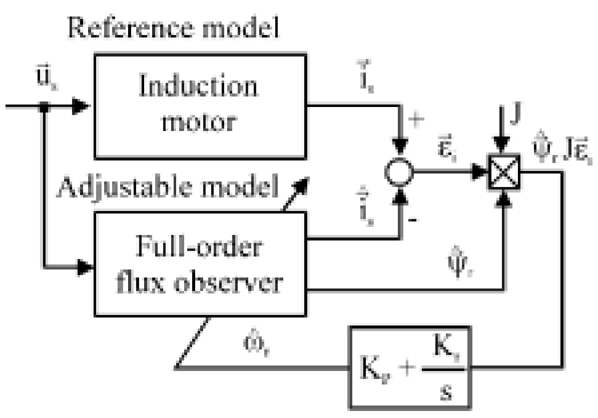

Fig. 1: Rotor speed estimation system

The speed-adaptive flux observer can be seen as a Model-Reference Adaptive System (MRAS) shown in Fig. 1. The reference model is the induction motor itself and the adjustable model is the full-order flux observer. The speed-adaptation law adjusts the estimated speed $\hat{\omega}_r$ based on the outputs of the reference model and the adjustable model. The adaptation law is the Proportional-Integral (PI) law.

OPTIMIZATION OF ADAPTATION PI GAINS

Design guidelines: From the analysis in frequency domain, Suwankawin and Sangwongwanich (2006) provide the design guidelines of the adaptation PI gains for the speed estimation as follows:

- The integral gain K_I is calculated from Eq. 4 for the specified tracking error δ of the ramp response

$$K_I=\frac{R}{\delta C^2 G'_{22}(s)|_{s=0}} \tag{4}$$

where, R is the acceleration or deceleration rate of the ramp, C is the amplitude of the rotor flux and transfer function $G'_{22}(s)$ is derived by Suwankawin and Sangwongwanich (2002) and its value versus ω_r and loads is shown in Fig. 2. As shown in Fig. 2, the value of $G'_{22}(s)|_{s=0}$ is not constant but related to the rotor speed and loads. The value of $G'_{22}(s)|_{s=0}$ is smaller in the low speed region than in the middle and high speed region. Beside this, when the loads of the motor increase, the value of $G'_{22}(s)|_{s=0}$ decreases, which mean larger K_I is needed to guarantee good tracking performance in heavy load condition and low speed region

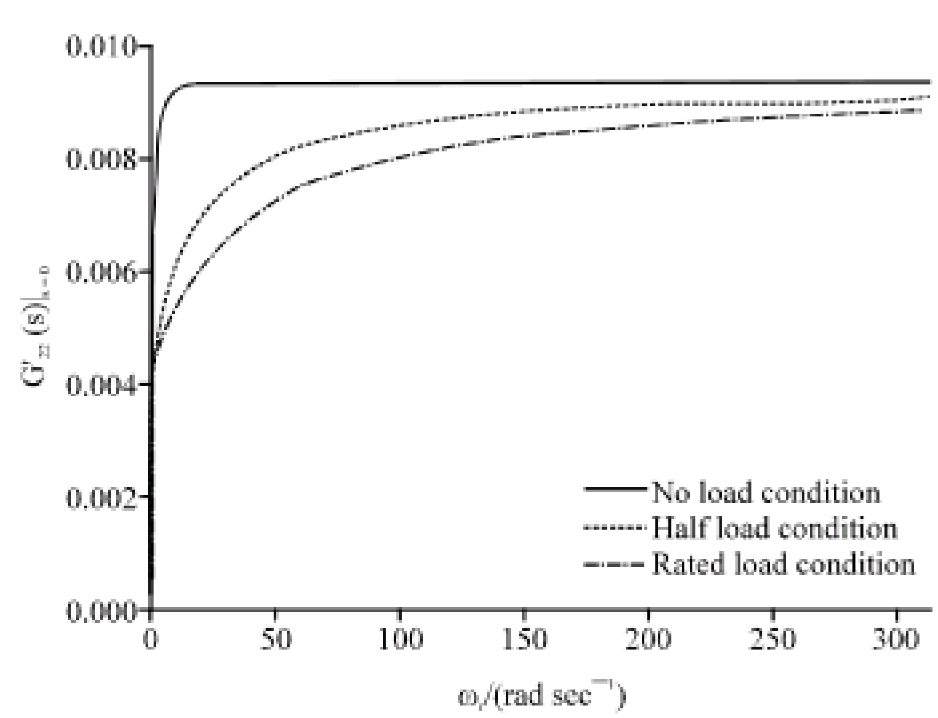

Fig. 2: Plot of the value of $G'_{22}(s)|_{s=0}$

- The corner frequency K_I/K_P is assigned to be less than the operating frequency to attain a sufficient phase margin as required
- The proportional gain K_P is calculated from the assigned corner frequency and the attenuation of high frequency noise η_q is checked using Eq. 5:

$$\left.\frac{\hat{\omega}_r}{\eta_q}\right|_{s=\infty} \cong CK_P \quad (5)$$

The guidelines imply that good tracking performance and low noise sensitivity of the speed estimation system depend on a large K_P and a small K_I, which is constrained by the requirement of a low corner frequency K_I/K_P. Therefore, a compromise needs to be made to achieve desirable performances of the speed estimation system. In this study, an optimization routine based on Genetic Algorithm (GA) is applied to make the compromise.

Optimization routine based on genetic algorithm: Genetic Algorithm (GA) is developed by Holland (1975). It is a stochastic optimization method based on the mechanics of natural evolution and natural genetics. It has been successfully applied to find a global optimum (Goldberg, 1989). A fitness function measures the fitness of the individuals to survive in a population. The GA operations, such as selecting, mutation and crossover, generate new generation of solutions at each cycle until the acceptable solution is obtained.

In this study, the basic genetic algorithm is applied to optimize the PI gains of the adaptive full-order flux observer. An optimization routine has been developed within the Matlab environment, which uses the genetic algorithm to seek the desirable PI gains automatically. The procedure of the routine is shown in Fig. 3.

Producing initial population is the first step of GA. In this study, the population is composed of the chromosomes that are real codes. Usually, the initial population is created random. In order to quicken the optimization routine, the calculated PI gains according to the design guidelines are also put in the initial population.

The corresponding evaluation of a population is called the fitness function. It is the performance index of a population. In this study, the fitness function is defined as the integral of the absolute value of the err between the measured rotor speed ω_r and the estimated rotor speed $\hat{\omega}_r$ as follows:

$$f(x) = \int_0^T \left|\omega_r(t) - \hat{\omega}_r(t)\right| \cdot dt \quad (6)$$

where, T is the evaluation period of the fitness function. In order to evaluate the tracking performance during

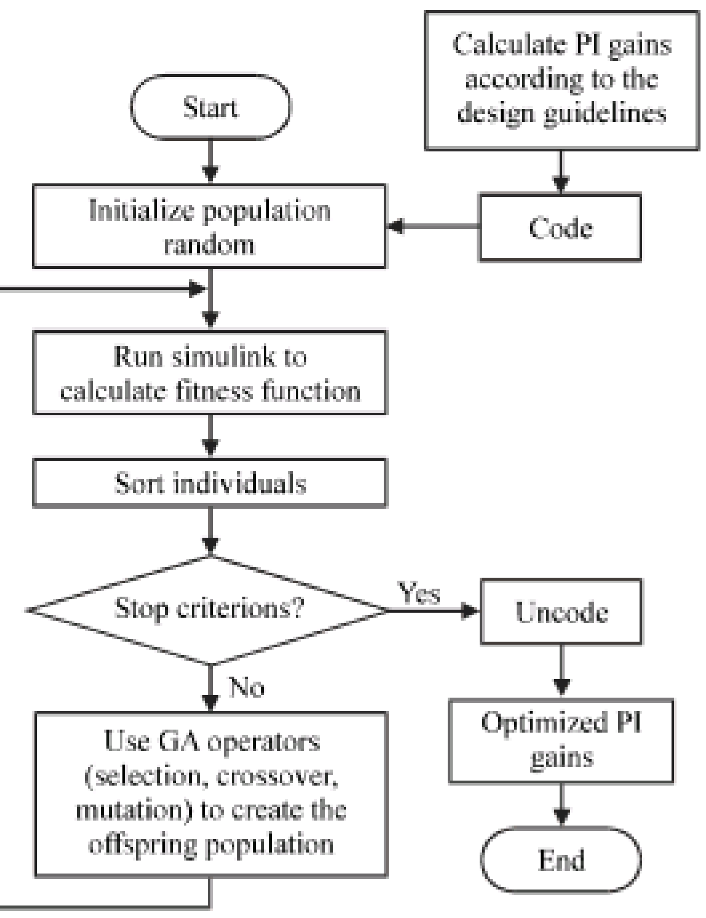

Fig. 3: Procedure of the optimization routine

acceleration/deceleration, the estimated error in steady state and the noise sensitivity of the speed estimation system, the speed reference input is set to be a periodic square wave. The period of the square wave is T, equaling to the evaluation period of the fitness function. When anyone of those performances is deteriorated, the fitness function will increase. Therefore, the above performances of the speed estimation system can be evaluated efficiently by calculating the fitness function.

After the fitness function is calculated, the fitness value or the number of the generation determines whether the evolution procedure is stopped or not. In this study the stop criterion is defined as:

$$f(x) \leq LIMIT \quad (7)$$

Where:

$$LIMIT = n\_ref \times 10\% \times N$$
$$N \quad = \frac{T}{T_s}$$

whrere, n_ref is the reference input of the rotor speed, N is the sampling time during the evaluation period of the fitness function and T_s is the sampling period. For example, in this study the evaluation period T = 0.3 sec, the sampling period T_s = 100 μ sec, then the sampling time N = 3000. If reference input of rotor speed n_ref = 1000 rmp, then the stop criterion is:

$$f(x) \leq 30000 \quad (8)$$

If the stop criterion is satisfied, the optimization routine will exit, otherwise, the new populations will be generated through selection, crossover and mutation.

Selection is a process to decide which individual will take part in reproducing offspring for the next generation according to its fitness value. In this study, tournament selection is applied. According to the defined fitness function here, the individuals with smaller fitness values will have larger probability to be selected. The best two individuals are selected to be the parents.

Crossover is a recombined operator for two high-fitness individuals (parents) to produce two offspring by matching their desirable quantities through a random process. The crossover occurs with certain probability which is called crossover probability. The crossover operation is applied to generate new chromosomes. In this study the equations of the crossover are:

$$\begin{aligned} X_{C1} &= X_{P1} + \alpha \cdot (X_{P2} - X_{P1}) \\ X_{C2} &= X_{P2} + \alpha \cdot (X_{P2} - X_{P1}) \end{aligned} \tag{9}$$

where, X_{P1}, X_{P2} are the parents chromosomes and X_{C1}, X_{C2} are the new generated chromosomes. α is a random real value from 0 to 1.

Mutation is a method to find the global optimum solution. It prevents the evolution from prematurity. In this study, the mutation operator is as below:

$$X' = X \pm 0.5 L \Delta \tag{10}$$

Where:

$$\Delta = \sum_{i=0}^{m} \frac{a(i)}{2^i}$$

where, X, X' is the chromosome before and after mutation. a(i) equals to 1 with probability 0.05 and equals to zero with probability 0.95. L is the maximal value of the individuals, in this study L = 65535.

Usually the mutation occurs with a small probability which is called mutation probability. But in this study, the mutation probability will equal to 1 if the evolution process gets into the prematurity, otherwise, it equals to 0.1. In this study, parameters used in GA are given below:

- Population size = 60
- Crossover probability = 0.9
- Mutation probability = 0.1 or 1

SIMULATION RESULTS

The optimization routine based on GA is used to seek the desirable PI gains for the speed estimation system. The parameters of the induction motor are shown in Table 1. In order to quicken the optimization routine, the calculated PI gains according to the design guidelines are put in the initial population.

If the initial population is created random absolutely, the optimization procedure is very slow and the final optimized PI gains are not good. As shown in Fig. 4. , after evolution over 500 generation, the stop criterion is still not satisfied. The result is $K_P = 12.255$, $K_I = 709.99$. The performance of the speed estimation system with this PI gains is shown in Fig. 5.

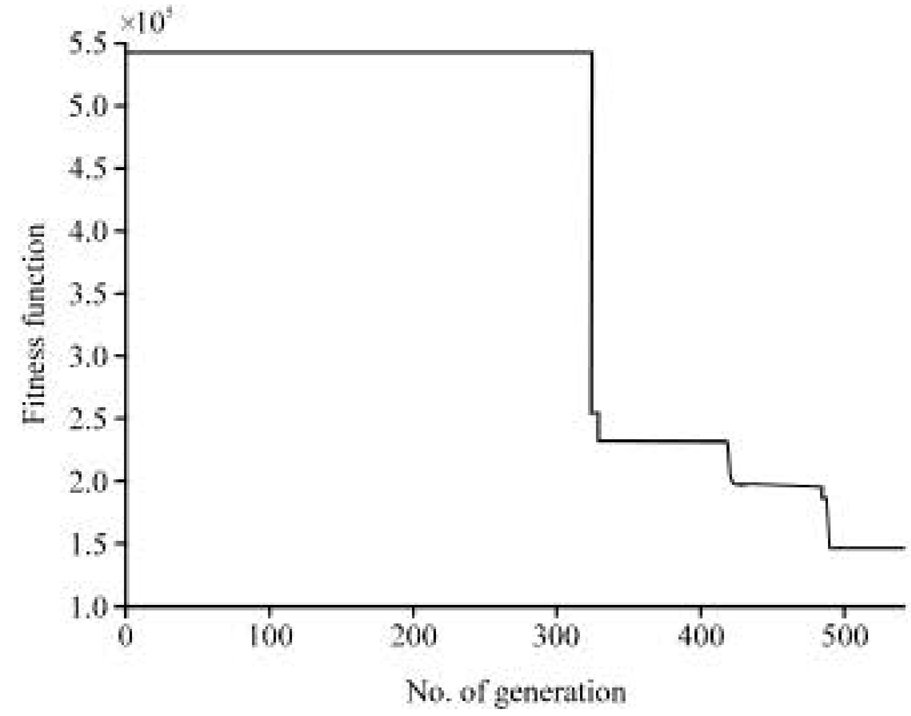

Fig. 4: Plot of the highest fitness function during evolution

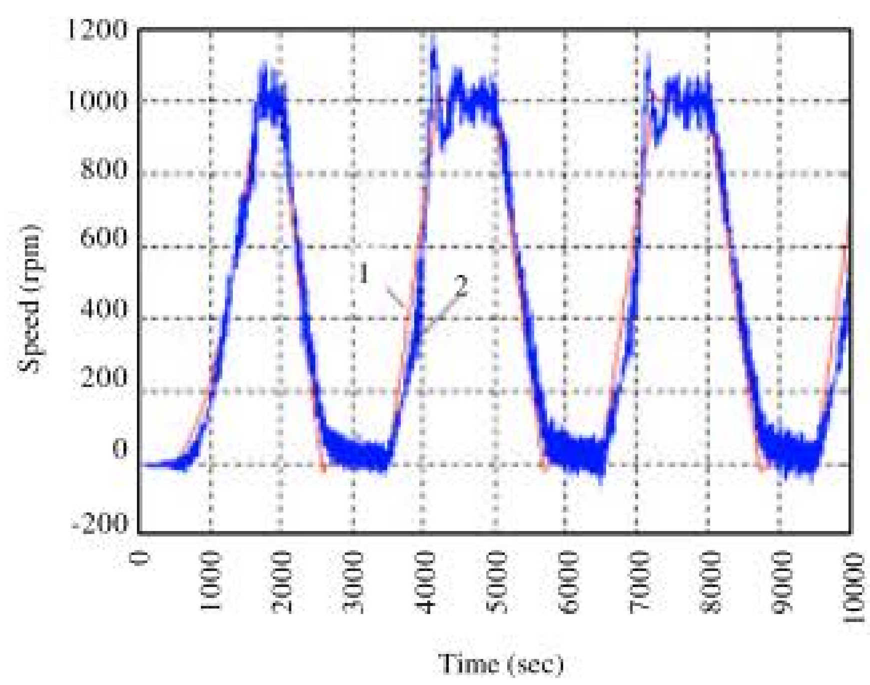

Fig. 5: Measured and estimated speed (K_P = 12.255, K_I = 709.99). Curve 1: Measured speed, Curve 2: Estimated speed

Table 1: Motor rating and parameters

Parameters	Rating
Power (kw)	2.2
Voltage (V)	220/380
Current (A)	4.9
Frequency (Hz)	50
Speed (rpm)	1430
Poles	4
Torque (N.m)	15
Stator Resistance R_s (Ohm)	2.804
Rotor Resistance R_r (Ohm)	2.178
Stator inductance L_s (mH)	330.03
Rotor inductance L_r (mH)	330.03
Mutual inductance L_m (mH)	319.7

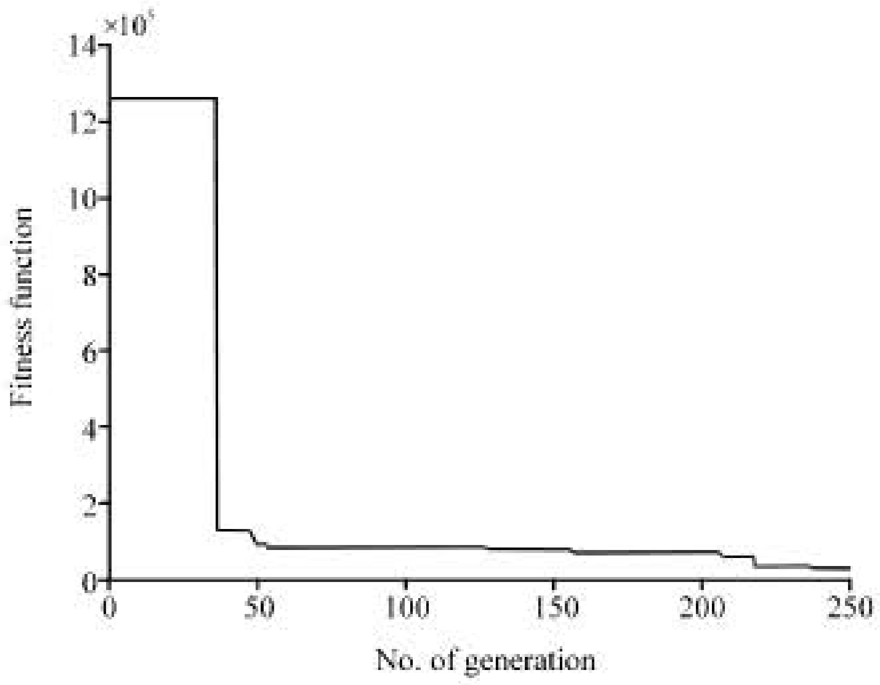

Fig. 6: Plot of the highest fitness function during evolution

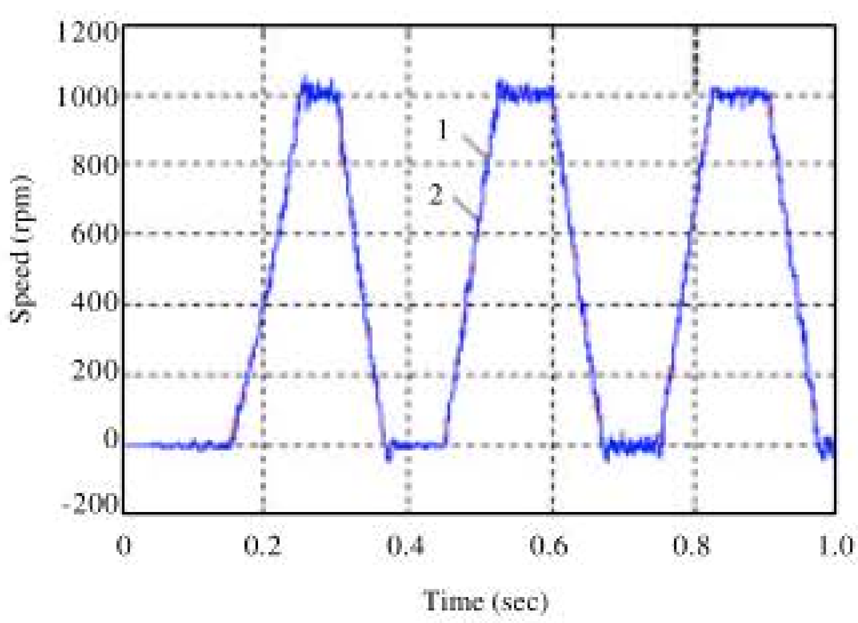

Fig. 7: Measured and estimated speed (K_P = 3.1587, K_I = 11047). Curve 1: Measured speed, Curve 2: Estimated speed

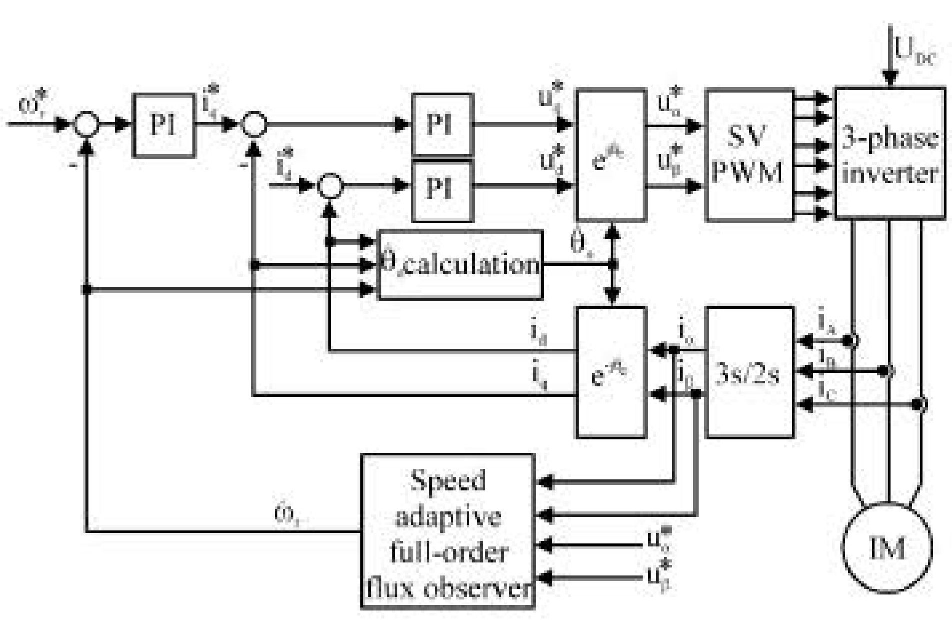

Fig. 8: Sensorless vector control system

If the calculated PI gains (K_P = 66.58, K_I = 13939) according to the design guidelines are put in the initial population, the optimization procedure is faster and the final optimized PI gains are desirable. As shown in Fig. 6, after evolution over 250 generation, the stop criterion is

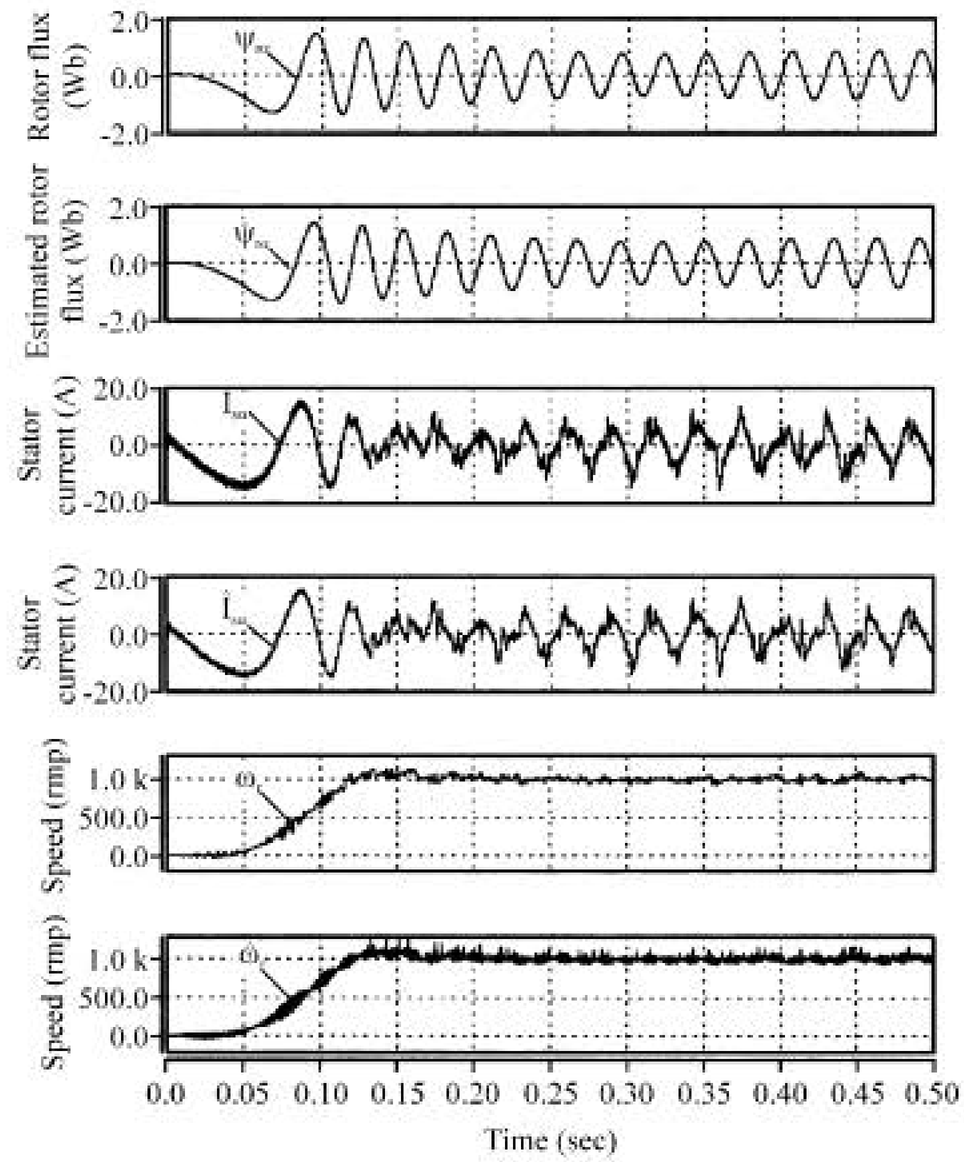

Fig. 9: Simulation results of the sensorless vector control system with PI gains tested by trial and error (K_P = 8, K_I = 4000)

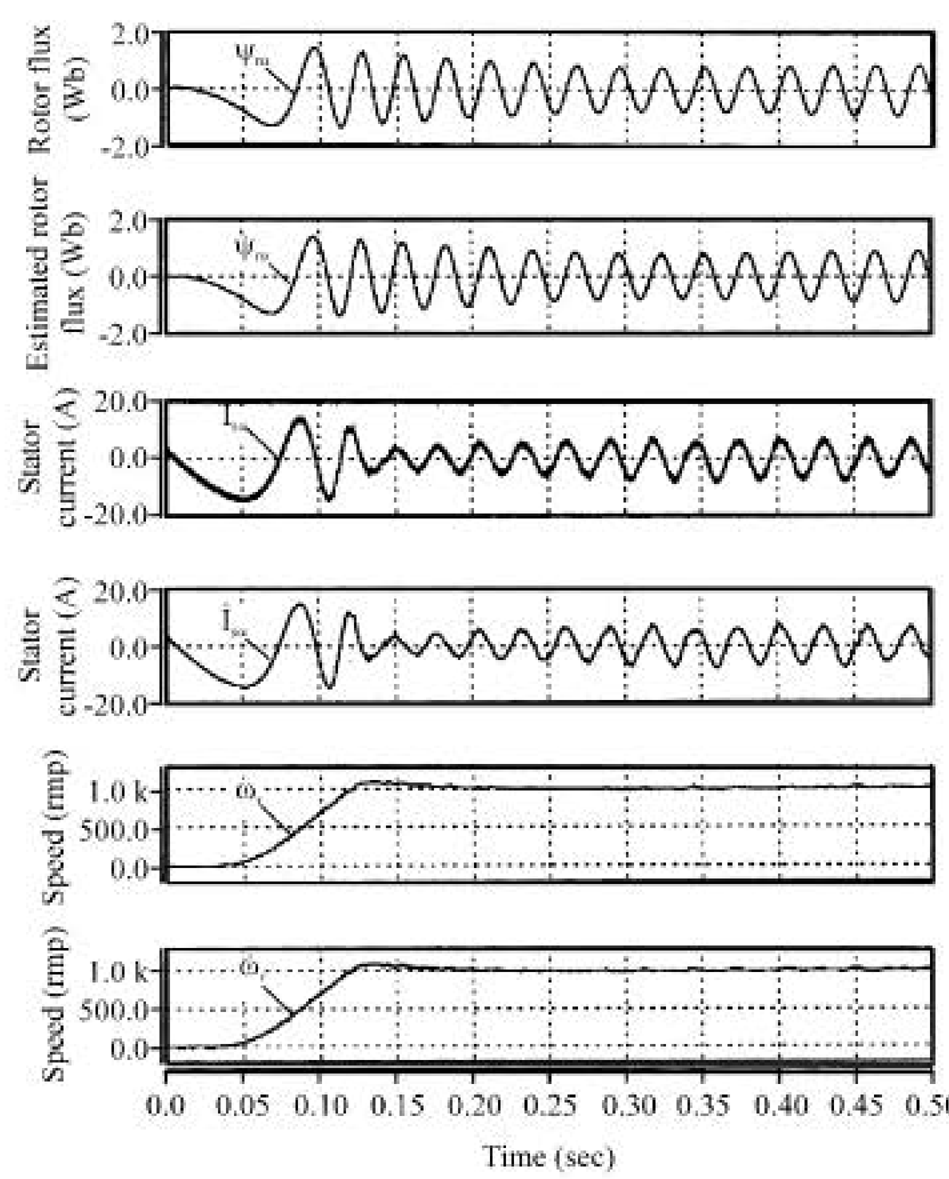

Fig. 10: Simulation results of the sensorless vector control system with the optimized PI gains (K_P = 3.1587, K_I = 11047)

satisfied. The result is K_P = 3.1587, K_I = 11047. The performance of the speed estimation system with this PI gains is shown in Fig. 7. The estimated speed tracks the practical speed well and the sensitivity of the noise in stator current is low.

Another simulation is done in order to compare the optimization effects of two method: (1) trial and error (usually used), (2) method proposed in this study. The optimized PI gains are applied to the sensorless vector control system (Fig. 8), respectively. The simulations are done in Saber and the results are shown in Fig. 9 and 10. The estimated speed in Fig. 9 is more sensitive to the noise than that in Fig. 10. Consequently, the noise in estimated speed distorts the stator current and deteriorates the orientation of the vector control system. Obviously, as shown in Fig. 10 the performance of the sensorless vector control system considering noise in current is good, which uses the PI gains optimized by the proposed method.

CONCLUSION

In this study, a new optimization method of the adaptation PI gains of the full-order flux observer in the sensorless induction motor drives is proposed. The new method employs an improved Genetic Algorithm (GA) based optimization routine that can be implemented off-line. A suitable fitness function is defined to assess the tracking performance, the noise sensitivity and the stability of the rotor speed estimation system when each individual's parameters are employed. The PI gains calculated according to the design guidelines are put in the initial population to quicken the optimization procedure. Using the proposed method, the desirable PI gains can be obtained and the optimization procedure is fast and efficient. Simulation results show that the estimated speed tracks the practical speed well when the optimized PI gains are employed, which validates the proposed method in the study.

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