**Control and Cybernetics**

vol. **36** (2007) No. 1

# Emotional learning based intelligent speed and position control applied to neurofuzzy model of switched reluctance motor

by

**Hossein Rouhani**[1,2]**, Arash Sadeghzadeh**[2]**, Caro Lucas**[2] **and Babak Nadjar Araabi**[2]

[1]Mechanical Engineering Department, University of Tehran
Tehran, Iran

[2]Control and Intelligent Processing Center of Excellence
Electrical and Computer Engineering Department, University of Tehran, Iran

e-mail: horouhani@ut.ac.ir, a.sadeghzadeh@ece.ut.ac.ir, lucas@ipm.ir, araabi@ut.ac.ir

**Abstract:** In this paper, rotor speed and position of a Switched Reluctance Motor (SRM) are controlled using an intelligent control algorithm. The controller is working based on a PID signal while its gain is permanently tuned by means of an Emotional Learning Algorithm to achieve a better control performance. Here, nonlinear characteristic of SRM is identified using an efficient training algorithm (LoLiMoT) for Locally Linear Neurofuzzy Model as an unspecified nonlinear plant model. Then, the Brain Emotional Learning Based Intelligent Controller (BELBIC) is applied to the obtained model. While the intelligent controller works based on a computational model of a limbic system in the mammalian brain, its contribution is to improve the performance of a classic controller like PID without much more control effort. The results demonstrate excellent improvements of control action in different working situations.

**Keywords:** intelligent control, emotion based learning, neurofuzzy models, switched reluctance motor.

## 1. Introduction

Switched reluctance (SR) motors have advantages due to their low cost, simple rugged construction, hazard-free operation and relatively high torque-mass ratio. They are ideally suited for direct-drive application because of their ability to produce high torques at very low speeds in contrast with other conventional motors (Alrifai, Chao and Torrey, 2003; Islam et al., Hwu and Liaw, 2001; Rahman et al., 2001; Xu and Wang, 2002). In addition, SR motors can work in a wide range of speeds without a noticeable reduction of efficiency. As they can yield high efficiency in a wide range of speeds with no need for a gearbox, SR motors are appropriate for use in many kinds of applications such as hybrid electric vehicles, machine tools, washing machines, fans and etc. Therefore, among all different kinds of electrical motors, Switched Reluctance Motors (SRM) have attracted much attention in recent years. SRM is a doubly salient single excited motor with no windings on rotor. Therefore, it has a high power per volume ratio. SR motors are designed for operation in deep saturation to increase the output power density. Due to saturation effect and variation of magnetic reluctance, all pertinent characteristics of the machine model (e.g. flux linkage, inductance, back EMF and produced torque) are highly nonlinear functions of both rotor position ($\theta$) and phase currents ($\boldsymbol{i}$) (Alrifai, Chow and Torrey, 2003; Islam et al., 2003; Hwu and Liaw, 2001).

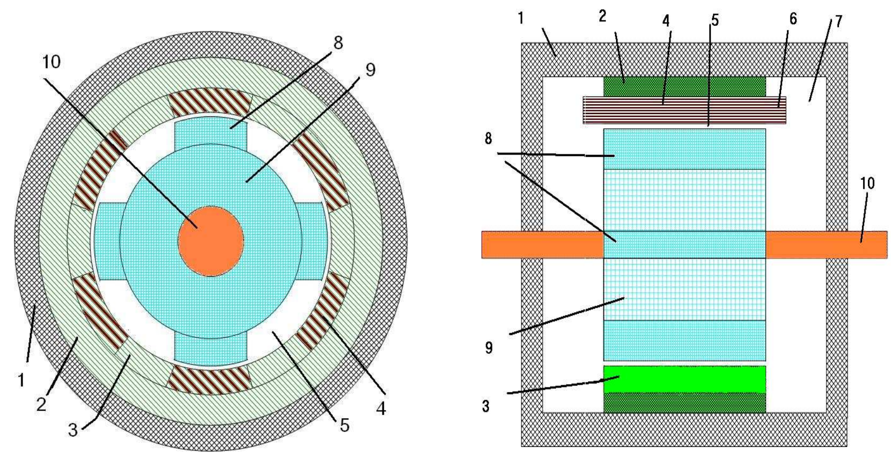


Figure 1. Two views of SR motor illustrating its various parts.
1-Frame 2-Stator yoke 3-Stator teeth 4-Windings 5-Air gap 6-Ending windings 7-Endcupping air 8-Rotor teeth 9-Rotor yoke 10-Axial shaft

Therefore, despite their simple mechanical construction (Fig. 1), SRMs need complex algorithms for control and commutation. Recent progress in intelligent feedback control and power electronics have led to a renewed interest in SR motor design problem from both theoretical and industrial points of view as an attractive alternative for the conventional induction motors. This paper focuses on solving these complex control problems via an innovative approach: use of Brain Emotional Learning Based Intelligent Control (BELBIC).

We have used BELBIC (Lucas, Shahmirzadi, Sheikholeslami, 2004; Milasi, Lucas, Araabi, 2004; Rouhani et al., 2006), our recently developed neuromorphic controller based on an emotional learning model elaborated in Moren, Balkenius

(2000), Balkenius, Moren (1998), to produce the control action. Biologically motivated intelligent computing has been successfully applied to solve complex problems in recent years,in which model-based approaches to decision making are being replaced by data-driven and rule-based approaches (Miyazaki et al., 1998).

In this research a cognitive approach of reinforcement learning is adopted in which a critic is permanently evaluating the performance of a control system on a plant. Indeed, for each system state, control performance is assessed based on an objective function and subsequently, reinforcement (or punishment) signal is created, which directs the control action by means of a learning algorithm (Lucas et al., 2000). This cognitive version of reinforcement learning can be interpreted as "Emotional Learning". Because, here, the reinforcement (or punishment) critic plays the role of some emotions such as stress, concern, fear, satisfaction, happiness and etc. in assessing and evaluating of environmental situations. This assessment is based on objectives in each concrete application (Lucas et al., 2000; Inoue, Kawabata, Kabayashi, 1996). Whether called emotional learning based control or reinforcement learning with critic, the approach is increasingly implemented in control engineering, robotics and decision support systems and has led to excellent results (Lucas, Shahmirzadi, Sheikholeslami, 2004; Milasi, Lucas, Araabi, 2004; Rouhani et al., 2006; Lucas et al., 2000; Inoue, Kawabata, Kobayashi, 1996; Fatourechi, Lucas, Khaki Sedigh, 2001).

In this paper, an intelligent controller will be applied to speed and position control of Switched Reluctance Motor (SRM). First, the nonlinear torque characteristic of SRM is identified using Locally Linear Model Tree (LoLiMoT) algorithm for training a neurofuzzy network (Nelles, 1996, 1997) and then Brain Emotional Learning Based Intelligent Controller (BELBIC) is applied to the plant. Use of a Neurofuzzy model of SR motor in this work proves the capability of BELBIC in controlling the plants with unstructured models. Using the proposed strategy, the speed and position control of switched reluctance has been tackled. The performance of the proposed controller is compared with that of a PID controller, which simulation results show better match for BELBIC. Aforementioned comparison seems to be more reasonable when the structure of BELBIC in this work is based on PID controller and the contribution of brain emotional learning will be performance improvement of PID controller.

## 2. The model of SR motors

The nonlinear properties of the SRMs are divided into two groups: nonlinear angular positioning parameters such as winding inductance, produced torque and Back EMF, which depend on the rotor angle and nonlinear magnetic characteristics, in which magnetic saturation causes the nonlinear magnetic characteristics. The modeling of SR motors is usually based on the magnetic-position curves, which show the linking flux versus phase current and rotor angular position. The mathematical model of SRM including the electromagnetic equations is achieved with considering the magnetic saturation (Alrifai, Chow, Torrey, 2003; Islam et al., 2003; Hwu and Liaw, 2001). The voltage equation in the motor phases is:

$$V_j = Ri_j + \frac{d\lambda_j(\theta, i_j)}{dt} + \frac{d\lambda_l}{dt} \tag{1}$$

where $V_j$ is $j^{th}$ phase winding voltage, $i_j$ is $j^{th}$ phase current, $\lambda_j$ is linking flux, $R$ is the ohmic resistance of phase winding and finally $\lambda_l$ is leaky linking flux. In (1) the linking coupling between adjacent windings is neglected. Using the chain derivation, (1) can be expressed as follows:

$$V_j = Ri_j + \frac{\partial\lambda_j(\theta, i_j)}{\partial i_j} \cdot \frac{di_j}{dt} + \frac{\partial\lambda_j(\theta, i_j)}{\partial\theta} \cdot \frac{d\theta}{dt} + \frac{d\lambda_l}{dt} \tag{2}$$

which can be written also as

$$V_j = Ri_j + L_{inc} \cdot \frac{di_j}{dt} + C_\omega \cdot \omega + L_k \cdot \frac{di_j}{dt} \tag{3}$$

where ($L_{inc}$) is the increasing inductance and ($C_w$) is the back EMF coefficient, and both of them are dependent on the phase current and rotor angular position. In this equation, ($L_k$) is the flux leakage. The produced torque on the shaft is obtained from the following equation:

$$T(i, \theta) = \sum_{j=1}^{n} \left(\frac{\partial W'}{\partial\theta}\right)_{i_j = cte} \tag{4}$$

where co-energy is determined as follows:

$$W'(i_j, \theta) = \int_0^{i_j} \lambda_j(i_j, \theta) \tag{5}$$

On the other hand, the mechanical equations are defined as follows:

$$\omega = \frac{d\theta}{dt} \tag{6}$$

$$\frac{d\omega}{dt} = \frac{1}{J}\left(T(i, \theta) - T_L - B.\omega\right) \tag{7}$$

where $\omega$ is angular velocity, ($T_L$) is load torque, ($B$) is friction coefficient, and ($J$) is the moment of inertia. However, finding a lumped function for ($T(i, \theta)$) is very difficult and demands numerical (FEM) or experimental data for each certain motor under study. Many efforts have been made to estimate the produced torque and linkage flux. However, as highly nonlinear functions, they were not obtained in the form of precise explicit formulae. On the other hand, neural networks are able to estimate the highly nonlinear functions via large number of neurons and consequently, they are not agile tools in online applications. Finally, locally linear neurofuzzy models are proven to be able to estimate highly nonlinear functions using less neurons than conventional neural networks such as MLP and RBF (Nelles, 1996, 1997; Jalili-Kharaajoo, Ranji, Begherzadeh, 2003). Here, an efficient and fast algorithm for training locally linear neurofuzzy networks entitled (LoLiMoT) will be proposed. LoLiMoT can be used in rapid training of neurofuzzy networks.

## 3. Locally linear model tree identification of nonlinear functions

The network structure of a local linear neurofuzzy model is depicted in Fig. 2. Each neuron realizes a local linear model (LLM) and an associated validity function (i.e. fuzzy membership function) that determines the region of validity of the corresponding LLM. The network output is calculated as a weighted sum of the outputs of the local linear models, where the validity functions are interpreted as the operating point dependent weighting factors. The validity functions are typically chosen as normalized Gaussians.

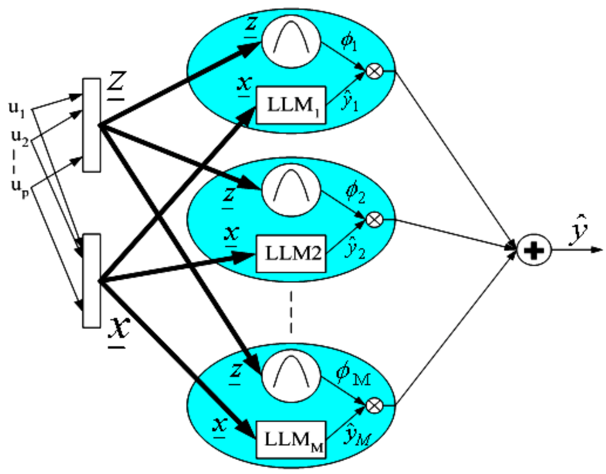


Figure 2. Network structure of a local linear neurofuzzy model with $M$ neurons for $n_x$ LLM inputs $x$ and $n_z$ validity function inputs $z$

The local linear modeling approach is based on a divide-and-conquer strategy. A complex SRM model is divided into a number of smaller and thus simpler subproblems, which are solved independently by identifying simple linear models (Nelles, 1996, 1997; Jalili-Kharaajo, Ranji, Begherzadeh, 2003). The most important factor for the success of such an approach is the division strategy for the original complex problem. This will be done by means of an algorithm named LoLiMoT (Locally Linear Model Tree).

LoLiMoT is an incremental tree-construction algorithm that partitions the input space by axis-orthogonal splits (Nelles, 1996). In each iteration, a new fuzzy rule or local linear model is added to the model. In each iteration of the algorithm, the validity functions which correspond to the actual partitioning of the input space are computed as the fuzzy membership functions and the corresponding rules are optimized by a local weighted least squares technique.

The training algorithm LoLiMoT is found out to be rapid, precise, self tuned and more user friendly than other conventional methods for training of neuro-fuzzy networks which makes it more acceptable in online control applications (Nelles, 1996, 1997; Jalili-Kharaajo, Ranji, Begherzadeh, 2003). The model based on this training algorithm is used in the following control problem.

For modeling the SRM, input-output data from finite element method or experiments can be used. Input data are rotor position and applied phase currents whereas the output is the produced torque. The torque is a function of phase current and rotor position. Therefore, the estimated function has two inputs (phase current, rotor position) and one output (produced torque).

Here, according to Fig. 3, a network including 50 neurons yields accurate results with 1% error. However, a network including 23 neurons with an error of 2% has been chosen to obtain more rapid performance in online control application. Fig. 4 shows normalized error for estimated produced torque in 1400 data sets ($0 < i < 50$ & $-\pi/4 < \theta < \pi/4$ ). Fig. 5 depicts the inputs and output data and Fig. 6 shows the local linear neurofuzzy model.

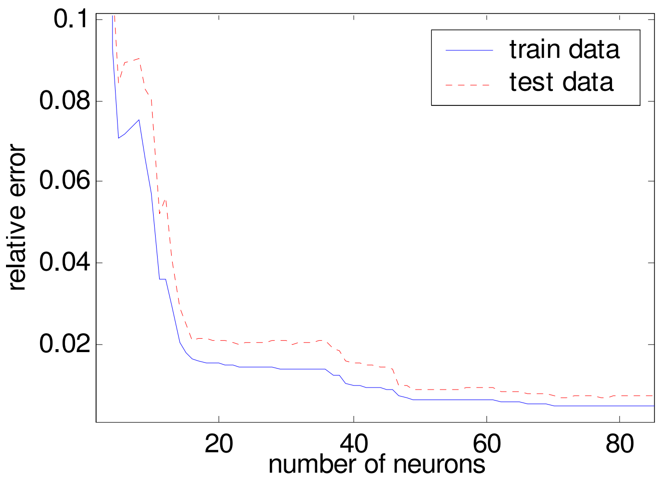


Figure 3. Convergence of network output to its target

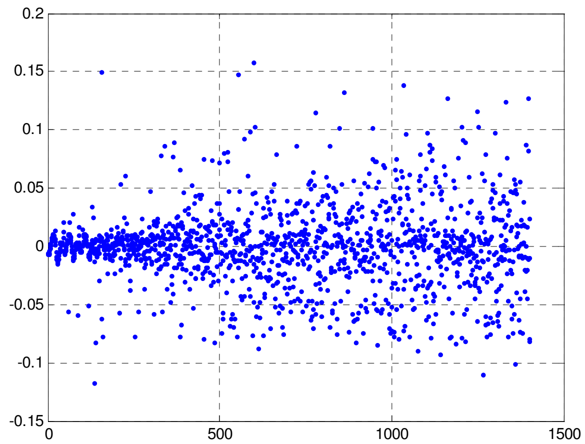


Figure 4. Normalized error for estimated produced torque in 1400 data sets

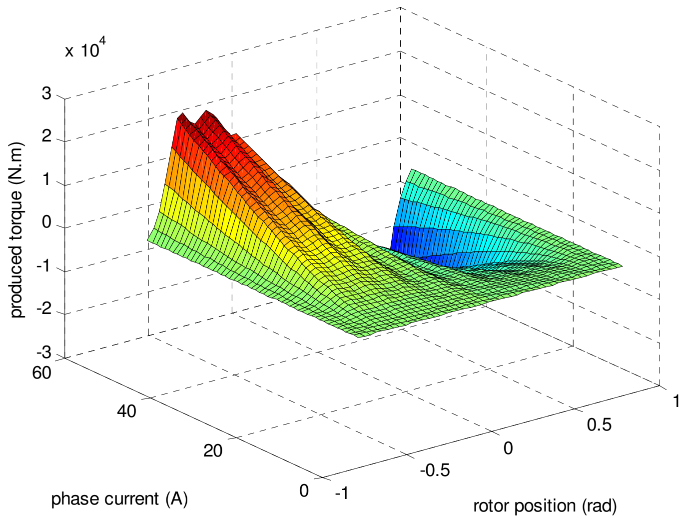


Figure 5. The input/output data

It should be noted once more that while performing faster and more precisely than traditional neural networks (e.g. MLP and RBF), locally linear neurofuzzy network trained by LoLiMoT presents a much more user-friendly function approximation method than look up tables. In other words, contrary to look up tables, in LoLiMoT the user is not obliged to spend much time on finding the

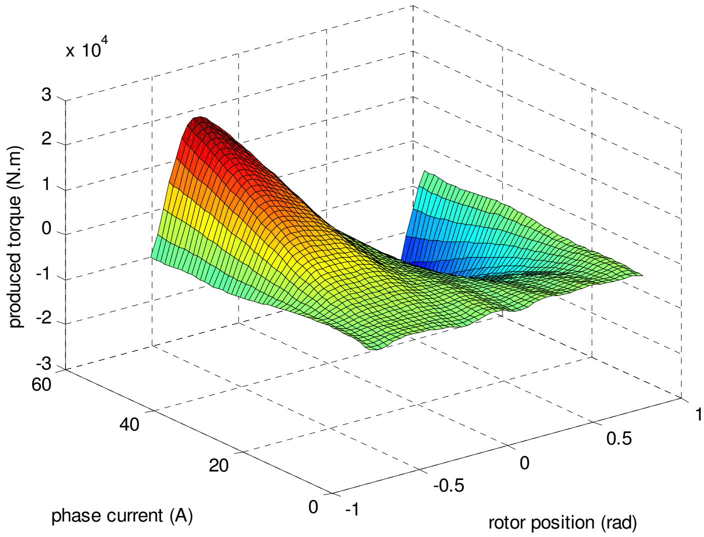


Figure 6. Local linear neuro-fuzzy model

model parameters by means of trial and error. Indeed, the LoLiMoT training method finds whole parameters of locally linear neurofuzzy model automatically. This effect is of a greater importance in online control problems.

## 4. Brain emotional learning based intelligent controller (BELBIC)

This research is motivated by the new successes and fruitful application results of functional modeling of emotions in control engineering, robotics and decision support systems. Here, a structural model based on the limbic system of mammalian brain in decision making and control is used. A network model developed by Moren and Balkenius (Balkenius, Moren, 1998; Moren, Balkenius, 2000) has been adopted as a computational model for the performance of Amygdala, Orbitofrontal Cortex, Thalamus, Sensory Input Cortex and generally, those parts of the brain thought to be responsible for processing emotions (Fig. 7).

There are two approaches in intelligent control: indirect and direct. In the indirect one the intelligent system is exploited to tune the parameters on the controller block while in the direct approach the intelligent system itself plays the role of controller. Unlike the previous application in which BELBIC was the controller block in terms of the direct approach (Lucas, Shahmirzadi, Sheikoleslami, 2004; Milasi, Lucas, Arrabi, 2004), in this work BELBIC is the tuner of overall loop gain of controller (Rouhani et al., 2006). Thus, basic per-

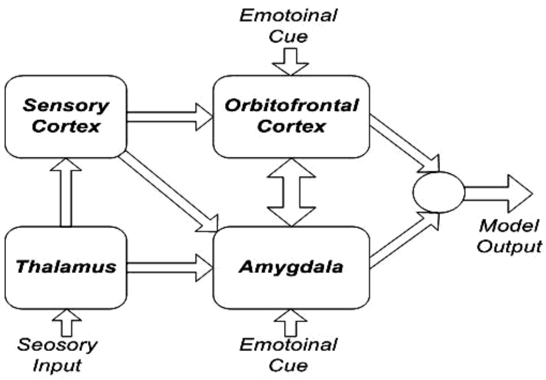


Figure 7. The abstract structure of the computational model mimicking some parts of mammalian brain

formance of the control system is influenced by the choice of primary controller block and BELBIC is in charge of overall loop gain tuning for that controller and generally, online and adaptive improvement of its performance. Of course, this improvement is admirable just when the final control effort will not be much more than its value before the performance improvement. In all, emotional learning based controllers have had an excellent response against uncertainties while having simple structure and being easily implemented.

As illustrated in Fig. 8, BELBIC is actually a control action generator mechanism based on two input signals: Sensory Input ($\boldsymbol{SI}$) and Emotional Cue ($\boldsymbol{EC}$). These two signals can be vectors in general however, in this case, are selected as two scalar values.

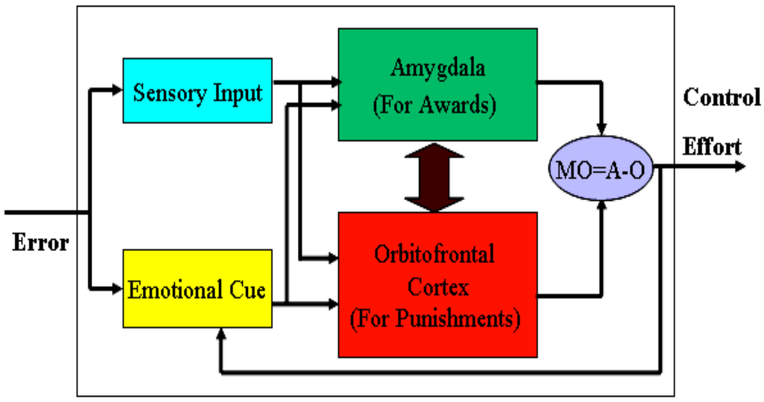


Figure 8. Control system configuration using BELBIC

Emotional learning is mainly taking place in Amygdala and Orbitofrontal Cortex. The learning rule of Amygdala is given in formula (8):

$$\Delta G_a = k_1 . \max\left(0, EC - |A|\right) \tag{8}$$

where $G_a$ is the gain in Amygdala connection, $k_1$ is the learning step in Amygdala and $EC$ and $A$ are the values of emotional cue function and Amygdala output at each time. The term max in the formula (8) makes the learning changes, monotonic. It implies that the Amygdala gain can never be decreased as it is modeled to occur in biological process (Moren, Balkenius, 2000; Balkenius, Moren, 1998). In other words, Amygdala can not unlearn the emotional signal which has been learned previously. Subsequently, the learning rule in Orbitofrontal Cortex is expressed as follows:

$$\Delta G_o = k_2 .(-EC) \tag{9}$$

which is inspired by the original biological process. Subtle deviations in formulae (8, 9) from the original version are done to make these processes symmetric in case of need to increase or decrease control effort to approach the set point. In the above formula, $G_o$ is the gain in Orbitofrontal connection, $k_2$ is the learning step in Orbitofrontal Cortex. Finally, the output of the whole model is calculated as follows:

$$MO = A - O \tag{10}$$

where, $O$ represents the output of Orbitofrontal Cortex. Indeed, BELBIC calculates the outputs of Amygdala and Orbitofrontal Cortex after receiving sensory input in formula (11,12) at each time:

$$A = G_a . SI \tag{11}$$

$$O = G_o . SI. \tag{12}$$

Generally Amygdala is responsible for reinforcement and Orbitofrontal Cortex is responsible for punishment. While Amygdala can never unlearn the emotional response it ever learned, inhibition of any inappropriate response of BELBIC is the duty of Orbitofrontal Cortex.

In order to exploit the computational model proposed by Moren and Balkenius in control applications, input signals in this model should be carefully built. In control application, the controller generally receives two signals as input signals (***SI*** and ***EC***) and yields the control signal via processing them in an online procedure. Therefore, these two signals have to be chosen in a way that have an apt interpretation in the closed loop control system.

The proposed structure for BELBIC as an emotional learning based controller is depicted in Fig. 8. In this structure, implemented functions for "Sensory Input" and "Emotional Cue" blocks are defined as follows:

$$EC = |MO|.(-W_1.\dot{e}e) \tag{13}$$

$$SI = W_2.e + W_3.\dot{e} + W_4.\int e\,dt \tag{14}$$

where $EC$, $MO$, $SI$ and $e$ are emotional cue, controller output, sensory input and output error and the $W_1$ through $W_4$ are the gains that must be tuned offline for designing a satisfactory controller. In the choice of these two signals ($\boldsymbol{EC}$, $\boldsymbol{SI}$) the following principles are taken into consideration:

1. Considering the output signal from BELBIC which is actually Sensory Input (SI) with an adaptively variable gain, one may conclude that $\boldsymbol{SI}$ has to have a "Control Signal" form which is adaptively reinforced (by Amygdala Block) or punished (by Orbitofrontal Cortex) based on Emotional Cue. Therefore, it is recommended to choose it as a standard function of output error such as PID. This choice has some benefits, like achieving a systematic way to tune parameters in the controller, which was the major difficulty in previous works (Lucas, Shahmirzadi, Sheikholeslami, 2004). In this way $k_1$ and $k_2$ are set at zero in beginning and then coefficients in $\boldsymbol{SI}$ signal will be found to yield a proper PID controller. Finally, $k_1$ and $k_2$ can be selected to reach the best improvement of PID performance for the determined $\boldsymbol{EC}$. Using this way, a challenge in BELBIC, consisting in coincident parameter choice, can be solved. Furthermore, the proposed controller structure is much more reliable because of presence of PID as a naturally robust classic controller. Particularly, even limited robustness of PID is more desirable for control of systems, which have model uncertainty, for example due to number of neurons used in system identification. Using lower number of neurons may be advantageous in reducing the sensitivity of model to noisy input data and, of course, the volume of online calculations in control applications. PID coefficients are defined by trial and error method in this work which can be defined even by an evolutionary optimization. This PID may not be the best, but it should be noticed that BELBIC is expected to improve the corresponding PID controller's performance adaptively.
2. When $\boldsymbol{EC}$ is a positive number, $G_a$ will increase (reinforcement) and when it is a negative number, $G_o$ will increase (punishment). In addition, a larger absolute value of $\boldsymbol{EC}$ causes a larger variation in reinforcement and punishment signals. Therefore, $\boldsymbol{EC}$ should have a larger absolute value when the error is large to motivate the control system to change in order to improve. Besides, it can be expressed generally that approaching a lower absolute error magnitude must be reinforced and in other words, getting far from the set point must be punished. Approaching the set point can be mathematically described by negative error derivative when the error is positive and positive error derivative when the error itself is

negative. The term of $-\dot{e}.e$ can provide all of aforementioned conditions. As $\boldsymbol{EC}$ is compared to $|A|$ in (8), it should have a proportional magnitude to $A$ or $\boldsymbol{MO}$ to make a logical subtraction in (8). Therefore, it has been multiplied by $|MO|$ to avoid the effect of its sign. Therefore, one can define the Emotional cue as in equation (13). Performance of BELBIC in adjusting SR motor's control gain may be more apparent through Fig. 9.

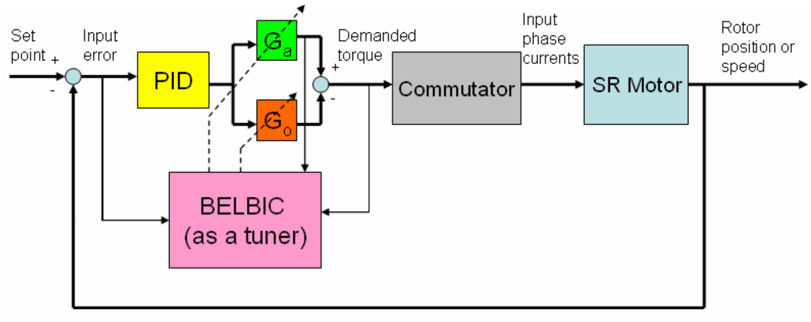


Figure 9. Performance of BELBIC in adjusting the gain of SR motor controller

## 5. Simulation results

In this section, the simulation results of the speed and position control problem using BELBIC with LoLiMoT identifier will be presented. The model obtained by algorithm LOLIMOT (Fig. 6) is substituted in equation (7).

Just like in other SR motor control algorithms, produced torque plays the role of the control effort. Phase currents are calculated according to the demanded torque and instant rotor position using a commutation algorithm. In this commutation algorithm, phase current rises and sets no steeper than a constant value determined by magnetic characteristics of the motor. Choosing the instant phase current is done with the aim of reaching the highest efficiency. Fig. 10 depicts the closed-loop system response using PID controller and using BELBIC as the emotional learning based adaptive PID controller. Comparing these two sets of results, one can realize that the performance of the system using BELBIC is considerably better than that of PID controller. The system responses using BELBIC is faster and BELBIC strategy causes faster and more precise response for close loop system compared to PID as the base of this intelligent controller. Also BELBIC controller did not make a greater control effort than PID controller (Figs. 11,12). In a more detailed description of BELBIC performance, reinforcement ($G_a$) and punishment ($G_o$) signals for speed control are depicted in Fig. 13. It can be seen that both approach a constant value in the steady state period. The negative punishment signal just works as a reinforcement signal. Why the reinforcement signal can not be negative? Just for reasons of mimicking the truth of a mammalian body. Similar results have been obtained in position control (Figs. 14-17).

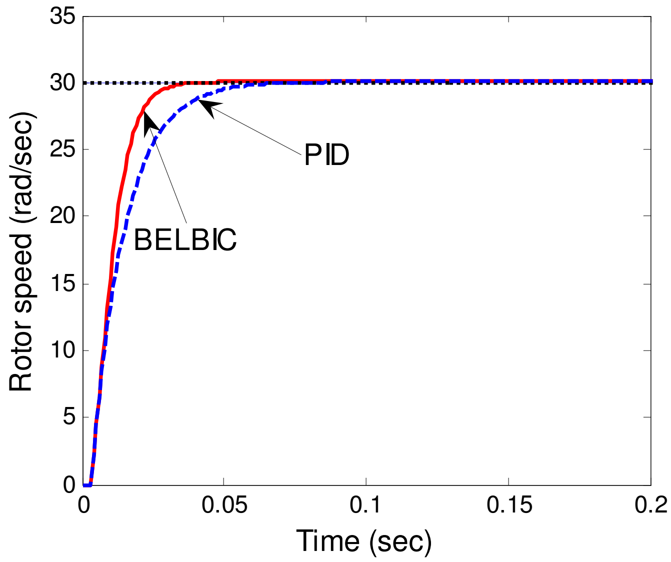


Figure 10. Rotor speed in speed control using BELBIC & PID

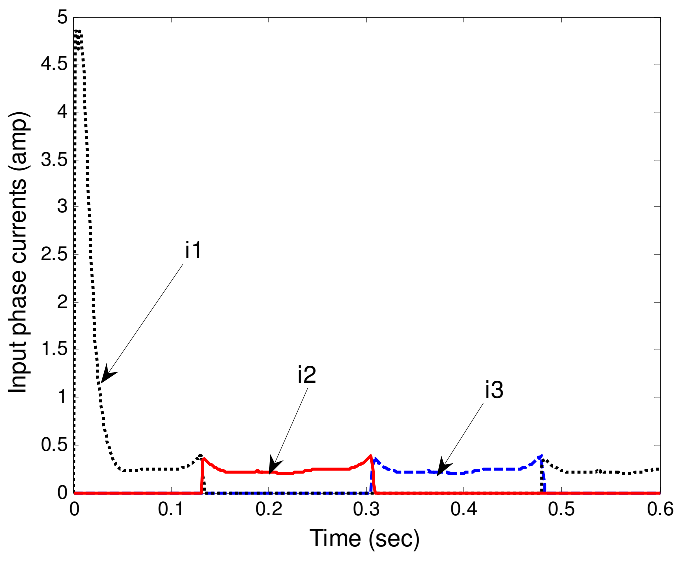


Figure 11. Input phase currents in speed control using BELBIC

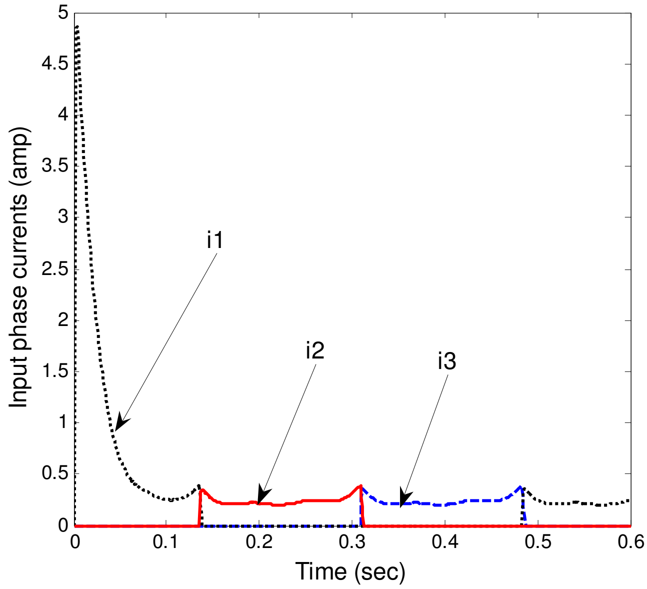


Figure 12. Input phase currents in speed control using PID

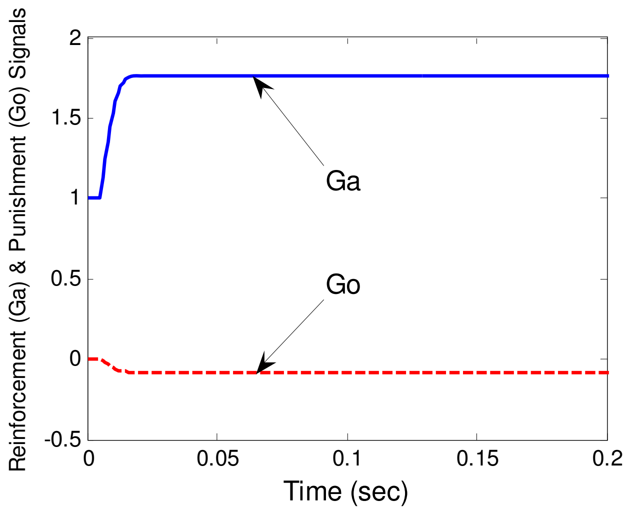


Figure 13. Reinforcement and punishment signals for speed control

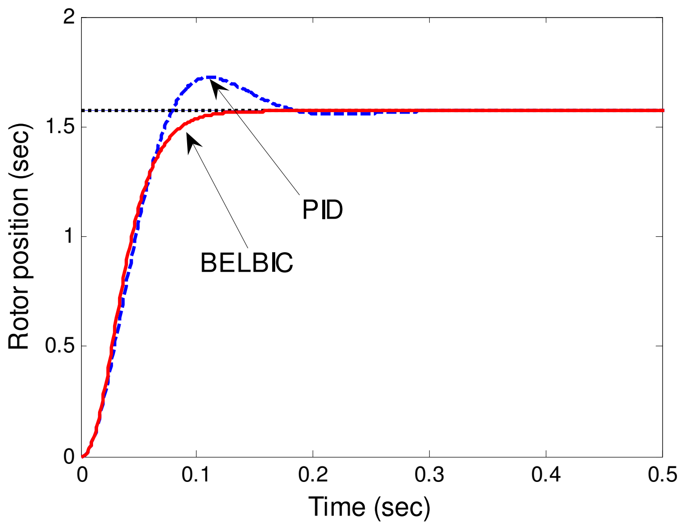


Figure 14. Rotor position in position control using BELBIC & PID

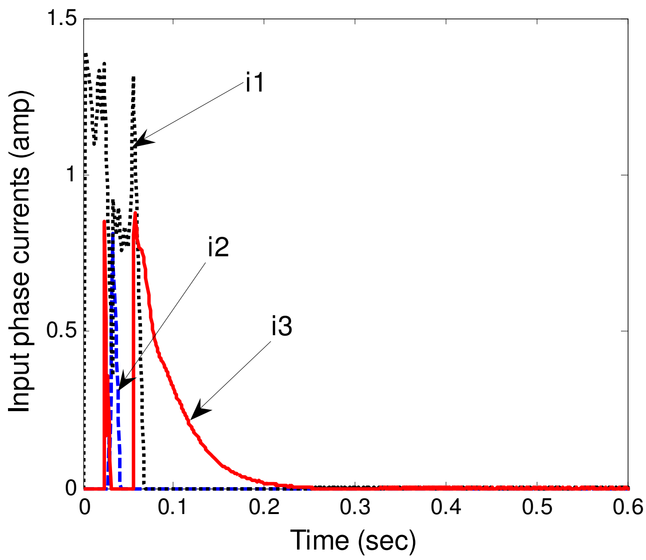


Figure 15. Input phase currents in position control using BELBIC

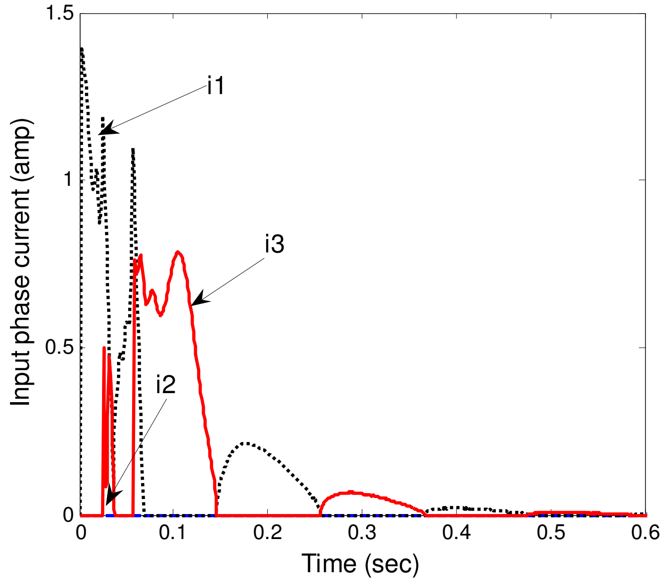


Figure 16. Input phase currents in position control using PID

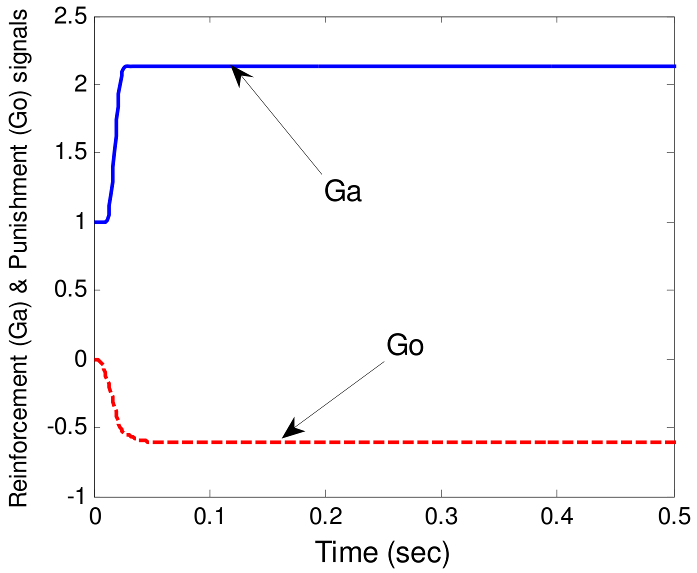


Figure 17. Reinforcement and punishment signals for position control

In addition, using PID signal as sensory input which can be reinforced or punished by BELBIC retains some advantages of PID controller such as robustness. As it is shown in Fig. 18 even when system is subjected to a variable load torque as noise, the performance of BELBIC is still very good (Fig. 19). Therefore, it can be claimed that BELBIC has enough robustness against noise and model uncertainties. Hence, it can be concluded that BELBIC with this structure based on PID as sensory input can retain many advantages of a conventional controller like PID and operates just like a Brain Emotional Learning Based Tuned Adaptive PID Controller. In order to study the performance of the proposed algorithm for emotional learning in the set point tracking, set point in speed control has been decreased and then increased. Controlled rotor speed and reinforcement-punishment signals are shown in Figs. 20,21, displaying symmetric performance of BELBIC in approaching the set point both in positive and negative directions. Figs. 18-21 also show the new tuning process once the system is affected by a new set point or disturbance after reaching the steady state situation.

Furthermore, the same architecture can be used in other applications, where the PID controller is replaced by the other conventional control strategies. In this application, this was not necessary because the persistent modifications introduced by BELBIC were enough to overcome the limitations of the PID controller due to the linear nature of the latter.

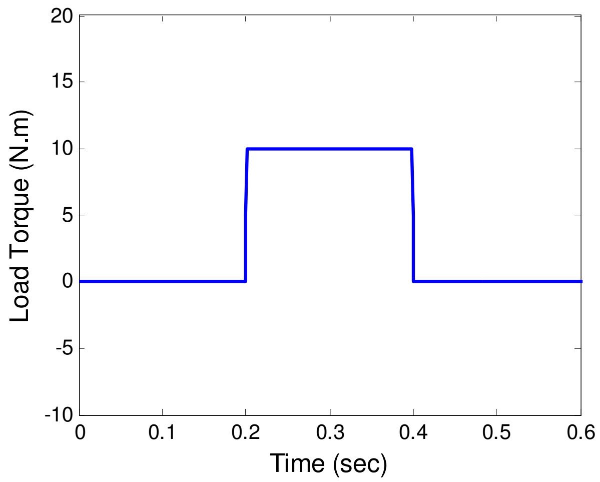


Figure 18. Imposed load torque as noise

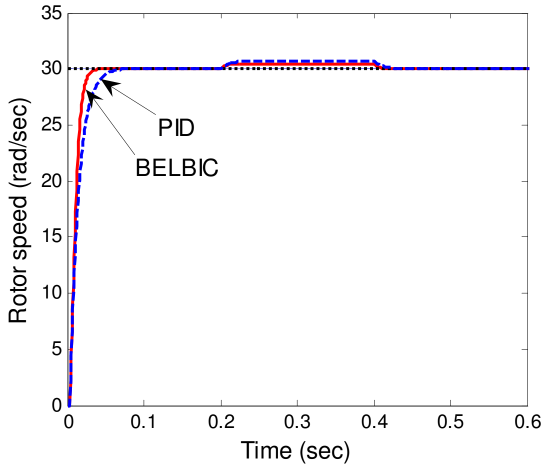


Figure 19. Rotor speed for the load torque of Fig. 18 controlled by means of BELBIC and PID

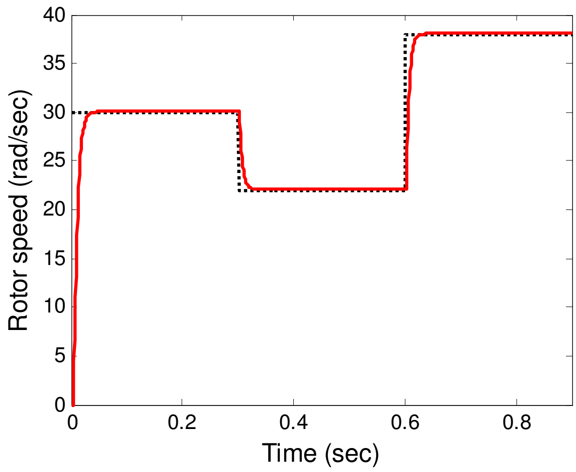


Figure 20. Controlled rotor speed for decreased and increased set point

## 6. Conclusion

In this paper, a Brain Emotional Learning Based Intelligent Controller (BELBIC) was applied to SR motor. To this end, the produced torque of the motor was estimated using Locally Linear Model Tree (LoLiMoT) algorithm. Then, BELBIC was applied to the system to tackle the speed and position control

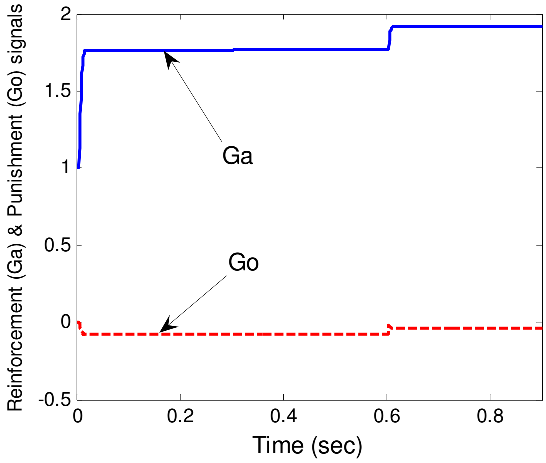


Figure 21. Reinforcement and punishment signals for speed control in the above decreased and increased set point

problem. The closed-loop system performance using BELBIC was compared with that of PID controller. It was shown that BELBIC could settle faster with less distortion while its control effort was not much higher than that of a PID controller. Also, selection of PID signal as sensory input of BELBIC could bring about some advantages, such as robustness against noise and model uncertainties, besides facilitating tuning. In simulation results, some other characteristics of the developed intelligent controller, such as its symmetric response to positive and negative set point approaching were demonstrated. Our use of BELBIC in this application also encompasses considerable improvement compared to our previous utilizations of this model, especially in terms of the required control efforts for achieving desired performance levels.

## References

Alrifai, M.T., Chow, J.H. and Torrey, D.A. (2003) Back-stepping nonlinear speed controller for switched reluctance motors. *IEE Proc. on Elect. Power Appl.* **150** (2), 193-200.

Balkenius, C. and Moren, J. (1998) Computational Model of Emotional conditioning in the Brain. *Proc. workshop on Grounding Emotions in Adaptive Systems*, Zurich.

Fatourechi, M., Lucas, C. and Khaki Sedigh, A. (2001) Reduction of Maximum Overshoot by means of Emotional Learning. *Proc. 6$^{th}$ Annual CSI Computer Conference*, Isfahan, Iran, 460-467.

Fatourechi, M., Lucas, C. and Khaki Sedigh, A. (2001) Reducing Control Effort by means of Emotional Learning. *Proc. 9th Iranian Conference on Electrical Engineering (ICEE2001)*, Tehran, Iran, 41-1 to 41-8.

Hwu, K.L. and Liaw, C.M. (2001) Robust quantitative speed control of a switched reluctance motor drive. *IEE Proc. Elect. Power Appl.* **148** (4), 345-353.

Inoue, K., Kawabata, K. and Kobayashi, H. (1996) On a Decision Making System with Emotion. *Proc. 5th IEEE International Workshop on Robot and Human Communication*, Tsukuba, Japan,461-465.

Islam, M.S., Husain, I., Veillette, R.J. and Batur, C. (2003) Design and performance analysis of sliding mode observers for sensorless operation of switched reluctance motors. *IEEE Transactions on Control System Technology* **11** (3), 383-389.

Jalili-Kharaajoo, M., Ranji, R. and Begherzadeh, H. (2003) Predictive Control of a Fossil Power plant Based on Locally Linear Model tree (LoLiMoT). *Proc. IEEE Conference on Control Applications (CCA'03* , Istanbul, Turkey, 1313-1316.

Lucas, C., Jazbi, S.A., Fatourechi, M. and Farshad, M. (2000) Cognitive Action Selection with Neurocontrollers. *Proc. 3rd Irano-Armenian Workshop on Neural Networks*. Yerevan, Armenia.

Lucas, C., Shahmirzadi, D. and Sheikholeslami, N. (2004) Introducing BELBIC: Brain Emotional Learning Based Intelligent Controller. *International Journal of Intelligent Automation and Soft Computing* **10** (1), 11-22.

Milasi, R.M., Lucas, C. and Araabi, B.N. (2004) A novel controller for power system based on BELBIC (Brain Emotional Based Learning Intelligent Controller). *Proc. World Automation Congress*, Seville, Spain.

Miyazaki, K., Araki, N., Mogi, E., Kobayashi, T., Shigematsu, Y. Ichikawa, M. and Matsumoto, G. (1998) Brain Learning Control Representation in Nucleus Accumbens. *Proc. 2nd International Conference on Knowledge-Based Intelligent Electronic Systems*, Australia, 1998, 21-23.

Moren, J. and Balkenius, C. (2000) A Computational Model of Emotional Learning in The Amygdala: From animals to animals. *Proc. 6th International conference on the simulation of adaptive behavior*, Cambridge, Mass., MIT Press.

Nelles, O. (1996) Local linear model tree for on-line identification of time variant nonlinear dynamic systems. *Proc. International Conference on Artificial Neural Networks (ICANN)*, Bochum, Germany, 115-120.

Nelles, O. (1997) Orthonormal Basis Functions for Nonlinear System Identification with Local Linear Model Trees (LoLiMoT). *Proc. IFAC Symposium on System Identification*, Kitakyushu, Fukuoka, Japan.

Nelson, L.G. (1964) *Theory and Technique of Variation Research*. Elsevier.

Rahman, K.M., Gopalakrishnan, S., Fahimi, B., Rajarathnam, A.V. and Ehsani, M. (2001) Optimized torque control of switched reluctance motor at all operational regimes using neural network. *IEEE Transactions on Industry Applications* **37** (3), 904-913.

Rouhani, H., Jalili-Kharaajoo, M., Nadjar-araabi, B., Eppler, W. and Lucas, C. (2006) Brain Emotional Learning Based Intelligent Controller Applied to Neurofuzzy Model of Micro Heat Exchanger. *Expert Systems with Applications*, (in press).

Xu, L. and Wang, C. (2002) Accurate rotor position detection and sensorless control of SRM for super high speed operation. *IEEE Transactions on Power Electronics* **17** (5), 757-763.