TSets Intelligent Controller for Electromechanical Positioning Actuators

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Abstract: - A cognitive intelligent approach to the control of an electromechanical positioning actuator using Tendentious Vague Sets (TSets) is presented.

The electromechanical positioning actuator prototype discussed is essentially a position control system whose constitutive elements are a PC based control unit, a Direct Torque Control (DTC) inverter and an induction motor.

A generalisation of the fuzzy sets known as TSets is used to incorporate learning abilities into the system required to control an electromechanical positioning actuator.

The synthesis of the controller is described, highlighting the practical implementation details.

An analysis of the resulting system intelligent behaviour is presented, including its learning ability. A comparison between the expected behaviour (simulation) and the obtained (experimental) is also presented.

Key-Words: - Intelligent Control, Position Control, TSets, Learning, Electromechanical Drives.

1 Introduction

Being a vanguard research subject in the area of electromechanical drives, the control of the angular speed of an induction motor has been the subject of many papers in recent years [1-2]. However, there are not many references to the angular position control of the induction motor. Higher cost motors, like Permanent Magnets, Variable Reluctance Machines (VRM) and Step Motors, are the most common selection for electromechanical positioning systems machines.

The development of intelligent controllers experienced a strong growing in the last decade. This can be explained due to its innate characteristics which allow, in a synthetic way, to control complex systems and/or difficult modelling ones. Nevertheless there is no normalisation in the development of these controllers, and several approaches are currently used. In the following sections, a controller is developed by using a cognitive approach supported on the Tendentious Vague Sets (TSets) theory[3].

In this paper we prove the learning capabilities of the TSets.

2 TSets Fundamentals

The motivation to the TSets development derives from analysis of the communication dialogue elements between linguistic emitters and receivers. Due to the implicit elements passed within a linguistic message, the credibility that the receiver attributes to the message should be considered an important element of a linguistic processing.

TSets incorporate this credibility factor with the creation of three membership functions named optimistic, pessimistic and tendentious. For a linguistic information they represent its possibility degree, impossibility degree and certainty degree, respectively.

2.1 TSet Definition

A tendentious vague set (TSet) is a generalisation of a fuzzy set, i.e. being X a set, $\breve{\breve{A}}$ is a tendentious vague set in X iif:

$$\breve{\breve{A}} = \left\{ \left(x, \left\{ \left[\mu^{o}_{\breve{\breve{A}}}(x), \mu^{1-p}_{\breve{\breve{A}}}(x) \right], \mu^{t}_{\breve{\breve{A}}}(x) \right\} \right) \Big|_{x \in X} \right\} \qquad (1)$$

where:

$\mu^{o}_{\breve{\breve{A}}} : X \rightarrow [0,1] : \mu^{o}_{\breve{\breve{A}}}(x) = \text{Degree}(x \in \breve{\breve{A}}) \in [0,1]$, is a membership function that measures the optimistic degree of membership of x to the set $\breve{\breve{A}}$, with $x \in X$. $\mu^{1-p}_{\breve{\breve{A}}}(x) = 1 - \mu^{p}_{\breve{\breve{A}}}(x)$ with $\mu^{p}_{\breve{\breve{A}}} : X \rightarrow [0,1] : \mu^{p}_{\breve{\breve{A}}}(x) = \text{Degree}(x \notin \breve{\breve{A}}) \in [0,1]$ is a membership function that measures the pessimistic membership degree (or non membership) of x to the set $\breve{\breve{A}}$, with $x \in X$ and $\mu^{t}_{\breve{\breve{A}}} : X \rightarrow [0,1]$, is a membership function given by:

$$\mu^{t}_{\breve{\tilde{A}}}(x) = \sqrt[\alpha]{\frac{\left[\mu^{o}_{\breve{\tilde{A}}}(x)\right]^{\alpha} + \left[\mu^{1-p}_{\breve{\tilde{A}}}(x)\right]^{\alpha}}{2|\alpha|}} \quad \text{with} \quad \alpha \neq 0 \qquad (2)$$

that measures the tendentious membership degree (or tendentious credibility) of x to the set $\breve{\tilde{A}}$.

The credibility factor α represents the credibility of an element in a vague set that can fluctuate from total disbelief (α → -∞) to total believe (α → +∞).

In this theory the following restrictions are always verified regardless of the x value.

$$\begin{array}{l} \mu^{o}_{\breve{\tilde{A}}}(x) + \mu^{p}_{\breve{\tilde{A}}}(x) \leq 1 \\ \mu^{o}_{\breve{\tilde{A}}}(x) \leq \mu^{t}_{\breve{\tilde{A}}}(x) \leq \mu^{1-p}_{\breve{\tilde{A}}}(x) \end{array} \quad \forall x \in X \qquad (3)$$

From (3) the previous restrictions it can be seen that TSets are a generalisation of the vague sets [4] and therefor also a generalisation of fuzzy sets.

Considering (1) and (3) some operations can be defined either by extension from the fuzzy sets either by using the TSets particular characteristics [3].

One of the most important tools in the usage of the TSets theory is to perform approximate reasoning. In the sequence of the generalised *modus ponens*, [5], the compositional inference rule using union and intersection operators can be written as:

$$\breve{\tilde{R}}(y) = \bigcup_{x} \left\{ \mathrm{I}\left[\left(\mu^{o}_{\breve{\tilde{A}}}, \mu^{1-p}_{\breve{\tilde{A}}}\right), \mu^{t}_{\breve{\tilde{A}}} ; \left(\mu^{o}_{\breve{\tilde{B}}}, \mu^{1-p}_{\breve{\tilde{B}}}\right), \mu^{t}_{\breve{\tilde{B}}} \right] \right\} \qquad (4)$$

being **U** any union operator and **I** any intersection operator. To reduce the calculation time, the most commonly used in electromechanical system are the maximum and the minimum.

2.2 Tendentious Vague Controller

By using the TSets its possible to develop a tendentious vague controller [6] with the ability to correct the behaviour on real time by using the credibility factor.

In the basic TSet controller (fig. 1), the tendentious vaguefication interface is the responsible for the quantization of the process state and for the tendentious vaguefication accordingly with the credibility factor (α). The knowledge base stores the linguistic rules in the conditional form, as well as some information about the universe of discourse. The tendentious devaguefication interface determines the final control action corresponding to the three scenarios. The decision making logic is responsible for the compositional inference. And the credibility evaluation determines the credibility factor variation accordingly with the three output scenarios.

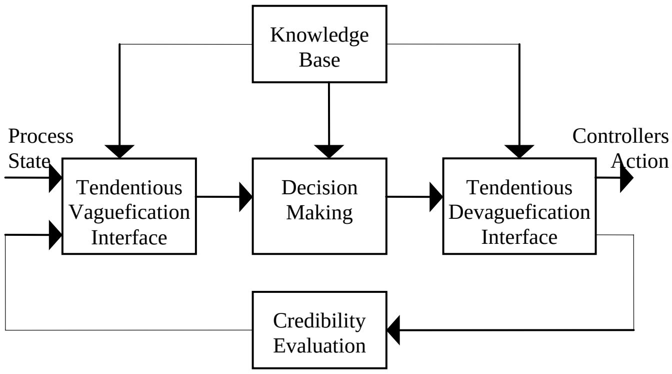

Fig.1 TSet controller functional block diagram

The main structural difference to the classical fuzzy controller [7], is due to the existence of an internal feedback loop inside the controller.

3 Cognitive Intelligent Controller

The intelligent control for electromechanical drives has been presented several times in the last years [8]. The usage of a set of techniques using artificial neural networks, fuzzy logic and genetic algorithms has allowed the inclusion of intelligent behaviour in electromechanical drives [9-10].

In fact, the use of artificial neural networks or fuzzy logic in the definition of control strategies is sometimes the basis to define an intelligent control. Nevertheless, this simplistic approach can not be considered when dealing with complex systems [11].

A generic systematisation can be made by including different approaches, namely the ones based in the observation of the human operators performance followed by its behaviour mimetism. It should also includes the human oriented machines approach.

With the usage of linguistic modelling, it is possible to model dynamic complex systems.

3.1 The Behaviour Levels of Intelligent Control Systems

The human behaviour has been discussed using different approaches. Considering the method based on the human capabilities [12], three levels of performance can be distinguished in the human behaviour limitations within deterministic environments: 1) skill, 2) rules and 3) knowledge level. (fig. 2).

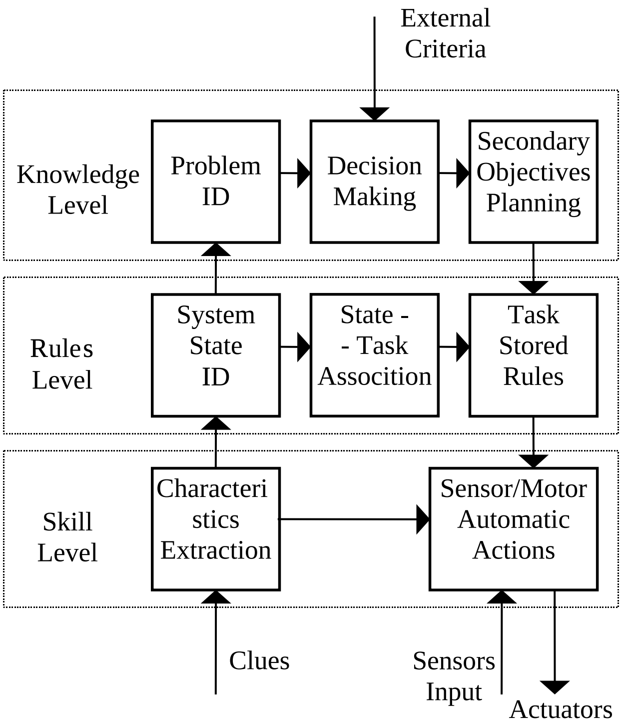

Fig.2 Human behaviour cognitive approach

The cognitive approach based in human mental models allows the identification of the components on the task development and simultaneously a certain degree of automatic implementation. The usage of this approach needs nevertheless the extra information that includes the definition of relevant knowledge and processing strategies.

3.2 Controller Development Stages

In order to synthesise a tendentious vague controller, with the structure presented earlier, a methodology can be defined by tasks corresponding to several stages. All of these tasks are at the rule level of intelligent behaviour, with the exception of the credibility evaluation. Therefor, the development of tendentious vague controller for position control methodology can be framed in each of the following intelligent behaviour levels.

3.2.1 State System Identification

The first stage in the development of the tendentious vague controller is to choose the input and output variables of the controller, i.e. to choose the process variables that should be observed and which of the control actions should be considered.

As with the non linguistic position controllers, usually, the chosen variables are the motor position error as well as its variation on a short time interval and the active torque, for the controllers inputs and output respectively.

The second stage in the development of the tendentious vague controller corresponds to the definition of the interface conditions, i.e., to the definition of the input and output variables representation in terms of linguistic sets (TSets).

The choice of the membership degrees for the optimistic and pessimistic membership is based in subjective criteria and a consequence of the analysis to the tendentious vague characteristics of the controlled system, nevertheless their choice does not have large influence on the robustness of the resulting controller. Therefor the chosen optimistic and pessimistic membership functions of the corresponding TSets (NG, NM, NR, ZE, PR, PM, PG,) can be represented generically by each of the following sets:

$$\begin{cases} \mu^{\mathrm{o}}_{\underset{\approx}{\mathrm{A}}}(\mathrm{u}) = \displaystyle\sum_{j=1}^{5} \frac{\xi_j}{\mathrm{u}_j} \\ \mu^{1-\mathrm{p}}_{\underset{\approx}{\mathrm{A}}}(\mathrm{u}) = \displaystyle\sum_{j=1}^{5} \frac{\delta_j}{\mathrm{u}_j} \end{cases} \qquad (5)$$

being u a generic element of the universe of discourse ξ the array that contains the optimistic membership degrees of the TSets, and δ the array that contains the pessimistic membership degrees of each TSet.

Graphically the partition of each of the linguistic variables is the one presented in figure 3.

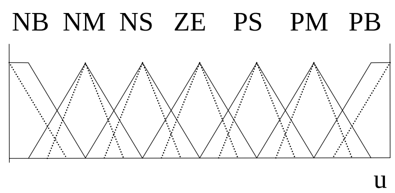

Fig.3 Linguistic universe of discourse partition

The universe considered for each of the input and output variables is a discrete one with 21 levels of quantization.

3.2.2 State-task Association

The third stage in the development of a tendentious vague controller corresponds to the definition of the knowledge base. At this level of behaviour this procedure coincides with the determination of which rules to apply in which circumstances.

There are several knowledge acquisition methods necessary to the formulation of the control rules [13]. In this controller, the option was to use a linguistic model of the system to control based on the desirable dynamic analysis of an electromechanical position controller in the extreme situation corresponding to an instantaneous step position reference variation.

The control rules are defined as conditional vague

statements like:
Premise: *Quantified_input_variable* is *Level_of_optimistic_membership* and *Quantified_input_variable* is_complementar to *Level_of_pessimistic_membership*
Implication: If *premise_variable_1* and *premise_variable_2* then consequence
Consequence: *Quantified_output_variable* is *Level_of_optimistic_membership* and *Quantified_output_variable* is_complementar to *Level_of_pessimistic_membership*

The otherwise is also used as a linking element to combine the different rules.

The linguistic control rules defined accordingly with the electromechanical positioning system dynamics and with the experimental knowledge of the closed loop electromechanical actuators are (tables 1 and 2),[14]. For instance for the element in the second line and fifth column:

If e = PS and Δe = NM then NM < χ < NS

where χ represents the output limits of the vague controller at that moment.

Table 1 Optimistic linguistic control rules

Δε ε	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NM	PS	PM
NM	NB	NB	NM	NS	NM	PM	PB
NS	NB	NB	NM	NS	NS	PM	PB
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NB	NM	PS	PS	PM	PB	PB
PM	NB	NM	PM	PS	PM	PB	PB
PB	NM	NS	PM	PM	PB	PB	PB

Table 2 Pessimistic linguistic control rules

Δε ε	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

On these tables the N, P, S, M and B are the membership short form notation of negative, positive, small, medium, and big, respectively.

3.2.3 Rule Usage During Task Execution

The fourth stage in the development of a tendentious vague controller corresponds to the definition of the tendentious vague inference algorithm, i.e. it corresponds to the linguistic controller generation of outputs for the optimistic and pessimistic scenario.

Since in this case the controller can be included in the MIMO category, with two inputs, ε and Δε, and two outputs, χ_{optim} and χ_{pessim}, then the linguistic rules can be written accordingly with table 1 and 2 by using the chosen tautology as follows:

Inputs: ε is E and Δε is ΔE
Rules:
Rule 1: If ε is NE and Δε is NE then $NB_1 < \chi < NB_2$
Otherwise rule 2: If ε is NE and Δε is NG then
$NB_1 < \chi < NB_2$
Otherwise rule 3: If ε is NE and Δε is NM then
$NB_1 < \chi < NB_2$
. . .
. . .
Otherwise rule 24: If ε is PE and Δε is PG then
$PB_1 < \chi < PB_2$
Otherwise rule 25: If ε is PE and Δε is PE then
$PB_1 < \chi < PB_2$

Consequence: $C\_optim < \xi < C\_pessim$

where E, ΔE, C_optim e C_pessim, are the values of the linguistic variables ε, Δε, χ_{optim} and χ_{pessim}, respectively (the index in the membership refers to the table used).

The fifth stage in the development of the tendentious vague controller is the tendentious devaguefication, and corresponds to the transformation of the vague tendentious actions into precise and deterministic ones. This action corresponds to the choice of the controllers non linguistic actions that better represent the possibility distribution of the control actions inferred, in this case corresponding to the optimistic and pessimistic scenario. The chosen strategy was the centre of gravity (COG). For a discrete universe of discourse, the non linguistic action is given by(6).

Since the controllers decision time is important in this electromechanical actuator, two decision lookup tables are used which include the outputs of the controller for all the possible input signals combinations.

$$c_o = \frac{\sum_{j=1}^{21} \mu_{\chi_o}(u_j).u_j}{\sum_{j=1}^{21} \mu_{\chi_o}(u_j)} \quad \wedge \quad c_{1-p} = \frac{\sum_{j=1}^{21} \mu_{\chi_{1-p}}(u_j).u_j}{\sum_{j=1}^{21} \mu_{\chi_{1-p}}(u_j)} \qquad (6)$$

The building of these tables can be done *à priori*, in order to reduce the controllers actuation time and simplify the real time procedures. These tables correspond to the limits of the controller action where there is no adaptive control or any type of learning, being the credibility factor (α) constant.

3.2.4 Knowledge Level Behaviour

The learning method used in this work is part of learning methods based on a merit attribution and, therefor, with reinforcement learning. This method uses an unsupervised learning algorithm and can be included in the methods that use linguistic inference learning.

The sixth and last stage in the development of this controller corresponds to the metric definition that allows the credibility evaluation of the obtained result by considering the optimistic and pessimistic results, in the following learning algorithm.

The learning algorithm used emulates a human learning model based on memory [15]. Accordingly with this model, the learning process can be seen as a information flux regulation through a duct that includes brief memory, persistent memory, and knowledge base, connected as shown in figure 4.

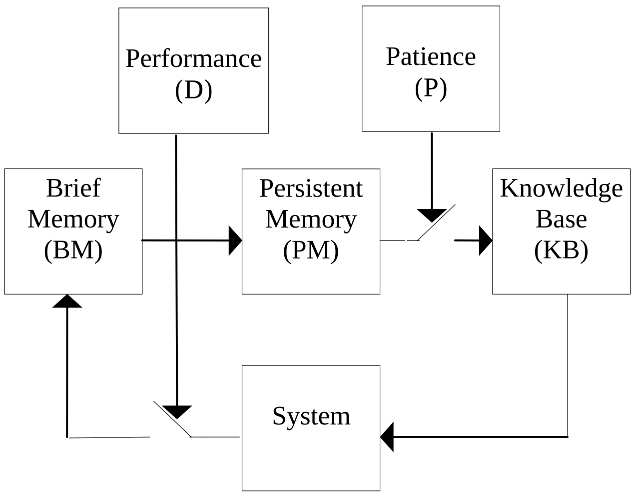

Fig.4 Memory based learning

The knowledge base (KB) is used by the indexing variables "ε" and "Δε", which depend on the actual error and error variation functions and that contained the output control variable. This knowledge base starts with the optimistic scenario, consequence of the tendentious devaguefication and with the learning process gradually tending to the tendentious one.

If no specific knowledge of the system is supplied to the controller then the starting KB will be empty.

Similarly to the KB the performance table (D) is used to evaluate the performance of the controller at any moment using for that purpose the actual values of "ε" and "Δε". Therefor the KB is adapted when a "bad" performance of the controller occurs, accordingly with the performance quality given by D. The D table is built considering the pessimistic scenario, consequence of the tendentious devaguefication.

The main objective of this learning method is to force the performance of the controller from an unsatisfying performance zone to a satisfying one.

4 Simulation Layout and Results

In order to simulate the controllers behaviour in this section, the block diagram of the simulated system (fig. 5) was implemented in the MATLAB® environment.

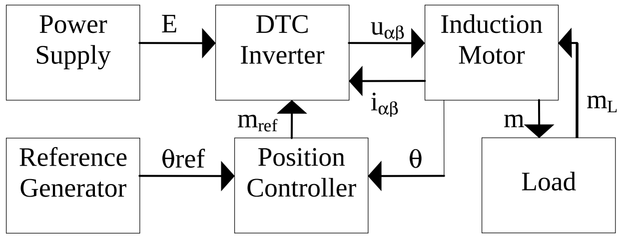

Fig.5 Model of the electromechanical actuator

The induction motor was modelled, considering the 3-fase induction machine model in the stationary referential αβ in p.u. (Appendix 2).

For the Direct Controller Inverter (DTC) the D strategy [2] was used in the selection of the voltage

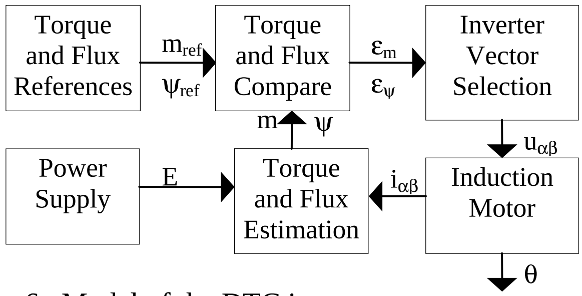

Fig.6 Model of the DTC inverter

In figure 7, (intelligent position controller model block), it is visible that the central element is the knowledge base which is stored into a lookup table for easy usage in real time. The initial knowledge base considered for the purpose of this simulation was empty, therefor emulating the total lack of knowledge from the system behaviour, and consequently the worst possible scenario.

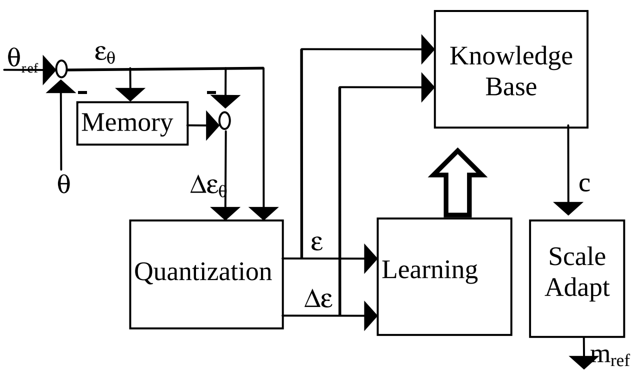

Fig.7 Intelligent position controller block diagram

The simulation result (fig. 8) of a sinusoidal positioning reference with 2rad (approx. 115º) of amplitude and with 1Hz frequency shows that the controller is able to learn and therefor after an initial learning stage (first and second signals), to follow the reference with minimum errors (third signal).

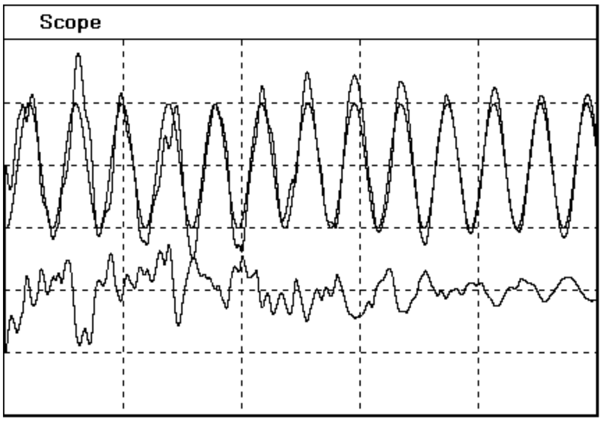

Fig.8 Position control simulation results

5 Experimental Prototype Layout and Results

To validate the previous simulation results, a experimental prototype was built (fig. 9).

The digital controller is implemented in a PC with a general purpose signal acquisition board. The software source developed (in graphical programming language "G"), presented a sequential structure.

The DTC inverter applies the derived torque with a delay of roughly 5ms.

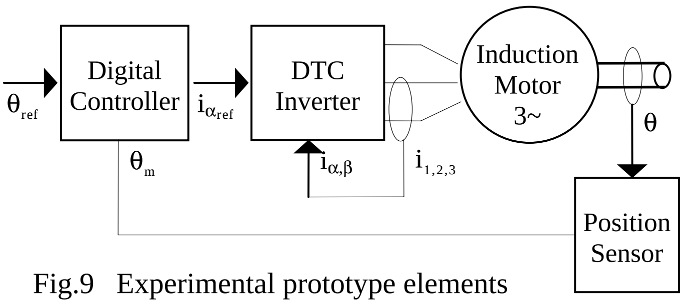

Fig.9 Experimental prototype elements

The position sensor used was an photoelectric incremental encoder with a 360 pulses per turn resolution. This sensor was chosen due to its robustness and frequency operation range up to 100kHz.

The electromechanical actuator position tracking result of a sinusoidal reference similar to the simulated one, in the beginning of the learning process, validates the simulation results and therefor the proposed method. The position tracking error during this tracking process (fig.10), shows that the controller can learn since no knowledge of the actuator was given to the controller in the starting stage.

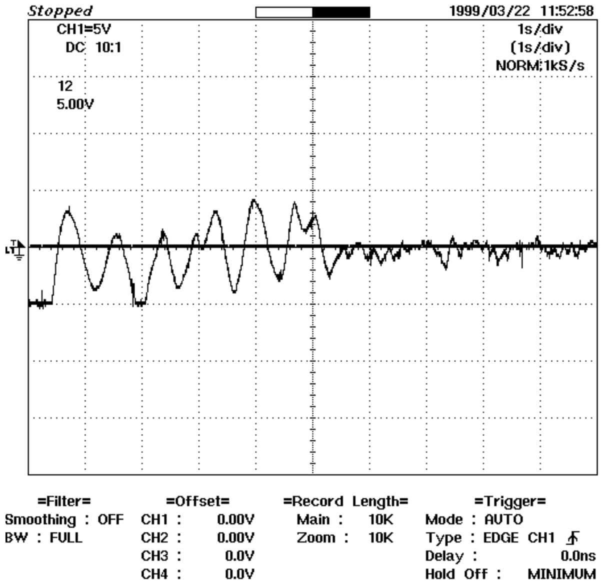

Fig.10 Starting experimental position tracking error results of a sinusoidal reference (Vertical Scale = 2 rad/div; Horizontal Scale =1 s/div)

6 Conclusion

In this paper an electromechanical positioning actuator, that uses TSets to incorporate cognitive knowledge, was presented. It was seen that TSets can emulate the real world uncertainties through the credibility degree that allows the internal self correction of the TSet controller and to increase the controllers intelligence, without resorting to laboratory experiments and allowing the creation of universal knowledge bases.

The controller synthesis, based in the intelligent human behaviour at the rule and knowledge levels, was presented. The controller synthesis stages allowed the inclusion of a learning algorithm that mimics a memory based learning human model.

Although the controller supporting development is very complex, its experimental implementation is quite simplified due to the knowledge base tables manipulation scheme used. The simulation and experimental results presented attested this behaviour, despite non modelled dynamics.

Appendix 1

Three phase induction motor data:

P_n= 1.5kW; N_n= 1380 rpm; f= 50Hz; U_n= 380V(⅄)
I_n= 3,9A; $\cos\varphi \in [0{,}53;\ 0{,}78]$; m_n= 10,4Nm; R_s= 5,745 Ω (at 25ºC); L_s= 65mH; J= 0,0037kg.m^2;

Appendix 2

Three phase induction model:

$$\begin{cases} u_{s\alpha} = r_s i_{s\alpha} + T_N \dfrac{d}{dt}(x_s i_{s\alpha} + x_M i_{r\alpha}) \\ u_{s\beta} = r_s i_{s\beta} + T_N \dfrac{d}{dt}(x_s i_{s\beta} + x_M i_{r\beta}) \\ 0 = u_{r\alpha} = r_r i_{r\alpha} + T_N \dfrac{d}{dt}\psi_{r\alpha} + \omega_m \psi_{r\beta} \\ 0 = u_{r\beta} = r_r i_{r\beta} + T_N \dfrac{d}{dt}\psi_{r\beta} - \omega_m \psi_{r\alpha} \\ \dfrac{d}{dt}\omega_m = \dfrac{1}{T_M}\left[\left(\psi_{s\alpha} i_{s\beta} - \psi_{s\beta} i_{s\alpha}\right) - m_L\right] \\ \dfrac{d}{dt}\theta = \omega_m \\ \psi_{r\alpha} = x_r i_{r\alpha} + x_M i_{s\alpha} \\ \psi_{r\beta} = x_r i_{r\beta} + x_M i_{s\beta} \end{cases}$$

where r_s is the stator resistance, r_r is the rotor resistance, x_s is the stator self-induction, x_r is the rotor self-induction, x_M is the mutual induction (being x determined as $x = L/L_{base}$), T_M is the acceleration constant ($T_M = J.\Omega_{base}/M_{base}$), T_N is the nominal time constant ($T_N = 1/\Omega_{snominal}$), m_L is the load torque, θ is the angular position, ω_m is the angular speed, i represents an electrical current, u a voltage and ψ one of flux components, the indices ‘r’ represent rotor quantities and the indices ‘s’ stator quantities, the α and β designate the coordinates of a referential solider with the stator (stationary).

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