A New Neurofuzzy Controller Based on NFN Networks

Marlon R. Gouvêa, Eduardo S. Figueiredo, Benjamim R. Menezes, Gustavo G. Parma, Anderson V. Pires, Walmir M. Caminhas

Abstract: **This work presents a new online learning controller, the ONFC (Online Neurofuzzy Controller), which has as base the *Neo Fuzzy Neuron* – NFN. Its principal difference from the most of the neurofuzzy structure used in control systems is the fact that the process error is not only used to correct the network parameters, but also as network input. Moreover, the ONFC has a very simple structure with only one input and one output, associated by two fuzzy rules. Other important characteristic presented by this controller is the reduced effort for the fixed parameters adjustment. The proposed controller development is presented for single and multi-loop control. This controller is applied for the control of two different plants. In a single loop control, simulations results are obtained for a generic plant with reverse characteristic. In a multi-loop control, the controller performance is evaluated through a practical implementation of an induction motor vector control with stator field orientation.**

Index Terms: **Fuzzy logic, neural network, neurofuzzy controller.**

1 INTRODUCTION

In complex applications where conventional controllers present difficulty, the fuzzy controllers are an attractive alternative, once they permit the use of qualitative aspects of human thinking. Many works can be found in literature related to these controllers, being more common works related to PI tuning [6, 10]. However, the performance of these systems depend on a specialist for convert the human expertise in "if then rules" and for adjustment of the membership functions.

The neural networks present characteristics of universal approximator [5], with learning capability and fault tolerance. In control applications, the neural networks normally are used to generate the control signal. The network parameters are adjusted in order to minimize the error between the reference and the real process output [8]. However, generally the neural networks can be seen as a black box, making difficult the use of previous knowledge.

Marlon Rosa de Gouvêa and E. S. Figueiredo are with the Steel Make Plant and Industrial Technology Departments, respectively, Gerdau Açominas S.A, phone 55 31 37492524, e-mails: marlon.gouvea@gerdau.com.br and eduardo.figueiredo@gerdau.com.br.

B. R. Menezes, G. G. Parma and W. M. Caminhas are with the Department of Electrical Engineering, Federal University of Minas Gerais – UFMG, e-mails: brm@cpdee.ufmg.br, parma@cpdee.ufmg.br, caminhas@cpdee.ufmg.br

The neurofuzzy systems have as main purpose to associate the capability of learning and fault tolerance from the neural networks with the qualitative aspects of human thinking from fuzzy logic.

A kind of neurofuzzy structure, the NFN (*Neo Fuzzy Neuron*), has been used successfully in many works related to fault detection [1], system identification and prediction [11, 13]. In this work, the NFN is used as base to develop a new controller structure. In this way, the next section makes brief revision of the NFN concepts. After that, the ONFC is developed for single and multi-loop control. The results obtained from simulation of a generic plant with reverse characteristic are presented. In sequence, practical results of the ONFC applied to induction motor vector control with stator field orientation – FOVS (Field Orientation Voltage Source) also are presented. In this case, the multi-loop control is evaluated, once the voltage component responsible by the torque production is obtained from ONFC's in a cascade configuration.

2 – ONFC DEVELOPMENT

2.1 – NFN networks

The NFN learning process consist of adjusting only the free parameters, which are connected to the neuron output, keeping fixed the membership parameters [1, 13], here called *fixed parameters*. The figure 1 presents the NFN structure.

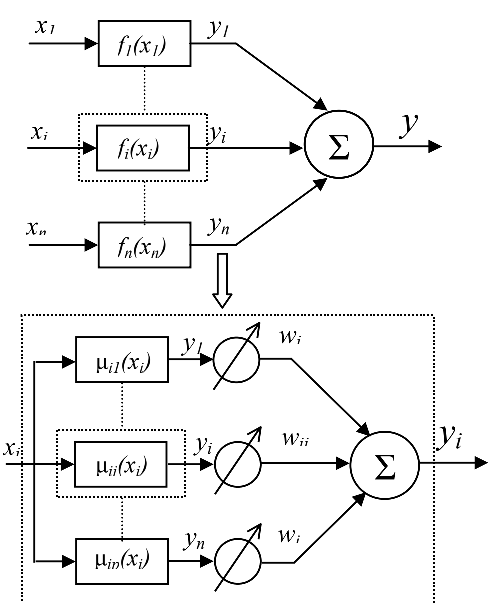

Figure 1 – NFN structure

The NFN membership functions are triangular and complementary. As consequence, for each input, only two rules are enabled in a given instant. The NFN output is obtained from equation (1) [1].

$$y = \sum_{i=1}^{n} y_i = \sum_{i=1}^{n} f_i(x_i) \tag{1}$$

The parameter corrections are made based on the gradient method, and equation (2) presents this process.

$$w_{ik_i}^{j} = w_{ik_i}^{j-1} - \alpha^{j} \frac{\partial e\left(w_{ik_i}^{j-1}\right)}{\partial w_{ik_i}^{j-1}} \tag{2}$$

2.2 - ONFC structure

An important characteristic presented by the proposed controller, the ONFC (*Online Neurofuzzy Controller*), it is a very simple structure, composed only by one input and one output associated by two fuzzy rules, as shown in figures 2 and 3. In this structure, the two membership functions are active during all control process, since its input does not exceed the limits of the universe of discourse. In this case, only one membership function is active, limited at the maximum fuzzy value, which is one.

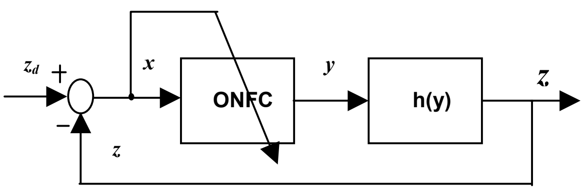

Figure 2 – ONFC in a single loop control

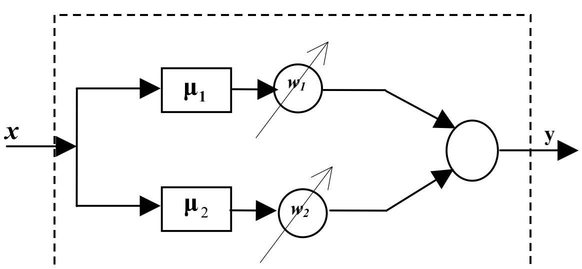

Figure 3 – ONFC internal structure

2.3 - ONFC in a single loop control
2.3.1 – Output calculation

The ONFC block diagram in a single loop control has been presented in figure 2. The controller output can be easily obtained from equation 3. The fuzzyfication process for the ONFC, with triangular and complementary membership functions, shown in figure 4, can be represented by equations (4) or (5) and (6), were x is the ONFC input, x_{rmax} and x_{rmin} are the universe of discourse limits, and y is the ONFC output.

$$y = \mu_1 w_1 + \mu_2 w_2 \tag{3}$$

$$\mu_1 = \begin{cases} -\dfrac{x}{\Delta_{\lim}} + \dfrac{1}{2} & x_{\min} < x < x_{\max} \\ 0 & x \geq x_{\max} \\ 1 & x \leq x_{\min} \end{cases} \tag{4}$$

Or

$$\mu_1 = \max\left[0,\ \min\left(-\frac{x}{\Delta_{\lim}} + \frac{1}{2}\ ;\ 1\right)\right] \tag{5}$$

$$\mu_2 = 1 - \mu_1 \tag{6}$$

Where:

$$\Delta_{\lim} = x_{\max} - x_{\min}$$
$$x = z_d - z$$
$$z = h(y)$$

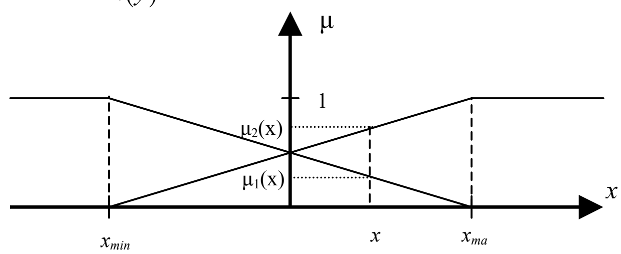

Figure 4 - ONFC fuzzyfication process

2.3.2 - Learning process

Like the NFN networks, the ONFC uses the gradient method in the learning process. In this way, the equation (7) defines the square error between the real and target output. The free parameters corrections are obtained from equation (8).

$$e = \frac{1}{2}(z - z_d)^2 \tag{7}$$

$$w_i(k) = w_i(k-1) - \alpha \frac{\partial e(k)}{\partial w_i} \qquad i = 1, 2 \tag{8}$$

Considering the chain rule,

$$\frac{\partial e}{\partial w_i} = \frac{\partial e}{\partial z}\frac{\partial z}{\partial y}\frac{\partial y}{\partial w_i} \tag{9}$$

Where:

$$\frac{\partial e}{\partial z} = (z - z_d) = -x \tag{10}$$

$$\frac{\partial y}{\partial w_i} = \mu_i \tag{11}$$

The second term in right side of equation (9) describes the plant dynamic, being function of each plant. In order to simplify the solution process of the equations (8) and (9), this term is incorporated in the learning factor, $\propto$, as represented by equation (12), where $\propto_o$ is considered a constant greater then zero.

$$\alpha_0 = \alpha \frac{\partial z}{\partial y} \quad (12)$$

From equations (8) to (12) the equation for the ONFC free parameter corrections is obtained:

$$w_i(k) = w_i(k-1) + \alpha_0 \mu_i x(k) \qquad i = 1, 2 \quad (13)$$

However, in equation (12), case the derived of the plant output in relation to the controller output is positive, the system error will be reduced. But, if this term is negative, the error will tend to increase [4]. These situations are summarized below:

If $\frac{\partial z}{\partial y} > 0 \quad e(k+1) < e(k) \Rightarrow$ error reduction

If $\frac{\partial z}{\partial y} < 0 \quad e(k+1) > e(k) \Rightarrow$ error increasing

Therefore, it is necessary to consider the signal variations of the plant output in relation to the controller output. The equation (14) presents the solution adopted to solve this problem, where *β* represent the learning factor considering this signal.

$$\beta = \alpha_0 \operatorname{sgn}(\Delta z) \operatorname{sgn}(\Delta y) \quad (14)$$

Where:

$\operatorname{sgn}(\Delta z) = 1$ for $\Delta z > 0$

$\operatorname{sgn}(\Delta z) = -1$ for $\Delta z < 0$

$\operatorname{sgn}(\Delta y) = 1$ for $\Delta y > 0$

$\operatorname{sgn}(\Delta y) = -1$ for $\Delta y < 0$

In this way, the final equation for correction the ONFC free parameters are obtained:

$$w_i(k) = w_i(k-1) + \beta \mu_i x(k) \quad i = 1, 2 \quad (15)$$

The equation (15) together with equations (3), (4) or (5) and (6) are the base to the practical implementation of the ONFC in a single loop control.

2.3.3 – Convergence analysis

Intuitively it is possible to realize that the control system convergence will occur when the ONFC input *x*, which represents the process error, turns zero. This will be formalized in sequence.

The condition where there are no free parameter adjustments is presented below:

$$\Delta w_i = w_i(k+1) - w_i(k) = \beta \mu_i x(k) = 0 \quad i = 1, 2 \quad (16)$$

Solving the equation (16) based on equations (4) and (6), for the condition $x_{min} < x < x_{max}$, it is obtained the following results, since *β* is assumed as a value previously adjusted in order to keeps the system stability:

$$\begin{cases} \Delta w_1 = \beta \left[\dfrac{-x^2}{\Delta_{\lim}} + \dfrac{x}{2} \right] \Rightarrow x(-2x + \Delta_{\lim}) = 0 \Rightarrow \begin{cases} x = 0 \\ x = \dfrac{\Delta_{\lim}}{2} \end{cases} \\ \Delta w_2 = \beta \left[\dfrac{x^2}{\Delta_{\lim}} + \dfrac{x}{2} \right] \Rightarrow x(2x + \Delta_{\lim}) = 0 \Rightarrow \begin{cases} x = 0 \\ x = \dfrac{-\Delta_{\lim}}{2} \end{cases} \end{cases}$$

Therefore, as can be observed from the results obtained above, the only condition that satisfies the equation (16), for $\Delta w_i = 0$, is $x = 0$.

2.4 - ONFC in a multi-loop control

Now, the ONFC application is extended for multi-loop control, with *n* controller in cascade configuration, as shown schematically in figure 5.

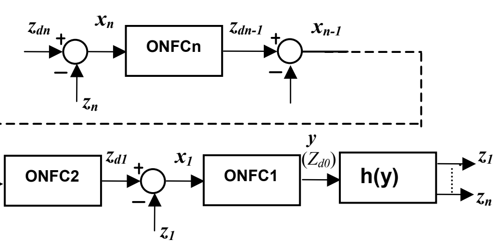

Figure 5 – ONFC in a cascade configuration

2.4.1 – Basic equations

The basic equations for ONFC are rewritten in a generic mode in order to facilitate the development of the equations for a cascade configuration of the proposed controller.

$$x_j = z_{dj} - z_j \quad (17)$$

$$e_j = \frac{1}{2}(z_j - z_{dj})^2 \quad (18)$$

$$z_{d_{j-1}} = \left(-\frac{x_j}{\Delta \lim_j} + \frac{1}{2} \right) w_{j1} + \left(\frac{x_j}{\Delta \lim_j} + \frac{1}{2} \right) w_{j2} \quad (19)$$

$$w_{ji}(k) = w_{ji}(k-1) + \beta_j \mu_{ji} x(k) \quad (20)$$

$$\beta_j = \alpha_j \operatorname{sgn}(\Delta z_j) \operatorname{sgn}(\Delta y) \quad (21)$$

Where

$i = 1, 2$

$j = 1 \rightarrow n$

2.4.2 – Equations development for ONFC in cascade configuration

First loop

For the first loop, the equations are the same already presented in the item 2.3. Therefore, the free parameters correction for this loop is obtained from equation (22):

$$w_{1i}(k) = w_{1i}(k-1) + \beta_1 \mu_{1i} x_1(k) \quad (22)$$

Second loop

Considering the chain rule, the gradient calculation for the square error between z_{d2} and z_2 as function of w_{2i} will be obtained from the equation (23).

$$\frac{\partial e_2}{\partial w_{2i}} = \frac{\partial e_2}{\partial z_{d_2}} \frac{\partial z_{d2}}{\partial y} \frac{\partial y}{\partial z_{d_1}} \frac{\partial y z_{d_1}}{\partial w_{2i}} \quad (23)$$

For the calculation of the third term in right side of equation (23), should be considered that z_{d0} is function of the output of all previous controllers connected in cascade. In this way, for the second loop, the output of the more internal controller, y (or z_{d0}), can be obtained from equation (24), where $x_1 = z_{d1} - z_1$.

$$y = \left(-\frac{x_1}{\Delta \lim_1} + \frac{1}{2} \right) w_{11} + \left(\frac{x_1}{\Delta \lim_1} + \frac{1}{2} \right) w_{12} \quad (24)$$

Solving equation (23) in the same way as equation (9), and considering the equation (24), the following solution is obtained:

$$\frac{\partial e_2}{\partial w_{2i}} = \frac{-x_2 \mu_{2i} (w_{12} - w_{11})}{\Delta \lim_1} \frac{\partial z_{d_2}}{\partial y} \quad (25)$$

Considering

$$\Delta_{w_1} = \frac{(w_{12} - w_{11})}{\Delta \lim_1} \quad (26)$$

The equation for the free parameters correction for the second loop can be obtained:

$$w_{2i}(k) = w_{2i}(k-1) + \beta_2 \Delta_{w1}(k-1) \mu_{2i} x_2(k) \quad (27)$$

As can be observed from equations (22) and (27), the free parameters in the more internal loop, in this case, w_{11} and w_{12}, must be different from zero when the correction process is initialized, once the weight of the more external controllers, depend on the weight of the more internal controllers.

n-th loop

Now, the equations for the ONFC in cascade configuration are generalized as shown bellow.

$$\frac{\partial e_n}{\partial w_{ni}} = \frac{\partial e_n}{\partial z_n} \frac{\partial z_n}{\partial y} \frac{\partial y}{\partial z_{d_{n-1}}} \frac{\partial z_{d_{n-1}}}{\partial w_{ni}} \quad (28)$$

$$\frac{\partial e_n}{\partial z_n} = -x_n \quad (29)$$

$$\frac{\partial y}{\partial z_{d_{n-1}}} = \prod_{j=1}^{n} \Delta_{w_{j-1}} \quad (30)$$

$$\frac{\partial z_{d_{n-1}}}{\partial w_{ni}} = \mu_{ni} \quad (31)$$

The equation (30) can be written in a simpler form as shown by equation (32):

$$\Pi_w = \prod_{j=1}^{n} \Delta_{w_{j-1}} \quad (32)$$

Where: $\Delta_{w0} = 1$

Finally, the generic equation for calculation of the free parameters adjustment of the *n-th* loop is obtained:

$$w_{ni}(k) = w_{ni}(k-1) + \beta_n \mu_{ni} x_n(k) \Pi_w (k-1) \quad (33)$$

3 – SIMULATION AND PRACTICAL IMPLEMENTATION

3.1 – ONFC applied in single loop control

This item presents the results obtained from digital simulation of a plant with reverse characteristic, with the ONFC in a single loop configuration. The system block diagram is shown in figure 6, and the equation (34) describes this plant [10].

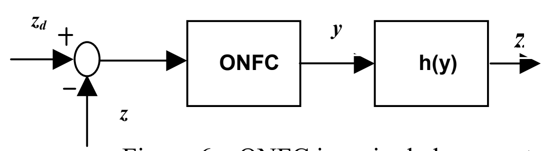

Figure 6 – ONFC in a single loop control

The figure 7 presents the system response for a step test. In the upper part of this figure, the target and real plant output are shown. The controller output is show in the lower part. The signal has opposite direction in relation to the output plant. It can be observed that the ONFC afforded a good response for the various steps applied.

$$z(k) = 1{,}4z(k-1) - 0{,}6z(k-2) + y^3(k-1) + 2y(k-1) + y^3(k-2) - 2y(k-2) \quad (34)$$

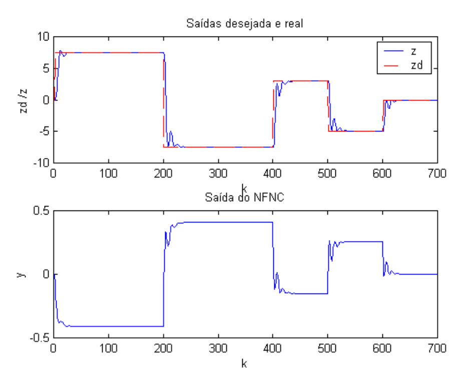

Figure 7 – Step response to a plant with reverse characteristics controlled by the ONFC

3.2 – ONFC applied in cascade loop control

In order to evaluate the ONFC performance in a cascade configuration, this item presents the results obtained from digital simulations and practical implementation of a vector control structure with stator field orientation – FOVS [12], for a 2 HP motor (Appendix A). The figure 8 presents the FOVS block diagram. As can be observed, the controllers for speed and torque are connected in cascade. The other control loop, responsible for the stator flux, it is an ONFC in a single loop configuration.

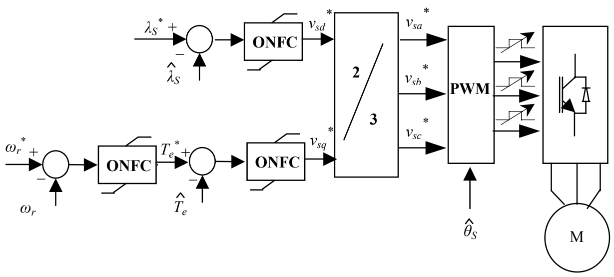

Figure 8 - Vector control structure using ONFC

At that point, a change in the learning process of the ONFC is presented in order to simplify the learning process represented by equation (33): the weight adjustment of each controller is proposed to be done from the more external controller to the more internal. The equation (35) represents the simplified learning process of the ONFC. As can be observed, the term represented by equation (32) is simply not considered.

$$w_{ni}(k) = w_{ni}(k-1) + \beta_n \mu_{ni} x_n(k) \tag{35}$$

In the next section, simulations results for two ONFC in cascade configuration will be presented in order to demonstrate that the proposed simplification does not produce significant changes in the controller performance.

3.2.1 – Simulation results

In this item, the use of equation (35) instead of equation (33) is evaluated through digital simulations. The figure 9 shows the simulation results considering equation (33). Four curves are presented: the stator flux amplitude - controlled in a single loop configuration, the speed - variable controlled by the external loop in the cascade configuration, the torque – variable controlled by the internal control loop, and the term Π_w (equations (32) and (33), where n = 2), that depends on the free parameters of the internal loop (torque controller).

The figure 10 shows the results obtained in the same conditions as obtained in figure 9, but in this case, using equation (35) for the ONFC free parameters correction of the speed controller (external loop). Comparing figures 9 and 10, it can be observed that the simplification proposed in equation (35) does not have significant effect in the control performance. Moreover, these simulation results highlight the good response obtained from the ONFC in the induction motor vector control, even during load variations.

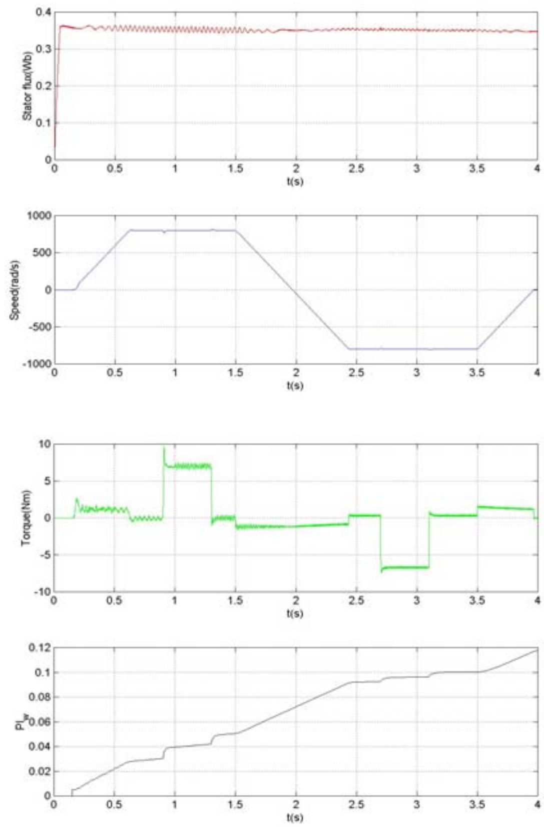

Figure 9 – Simulation: Results considering equation (33) for ONFC free parameter corrections

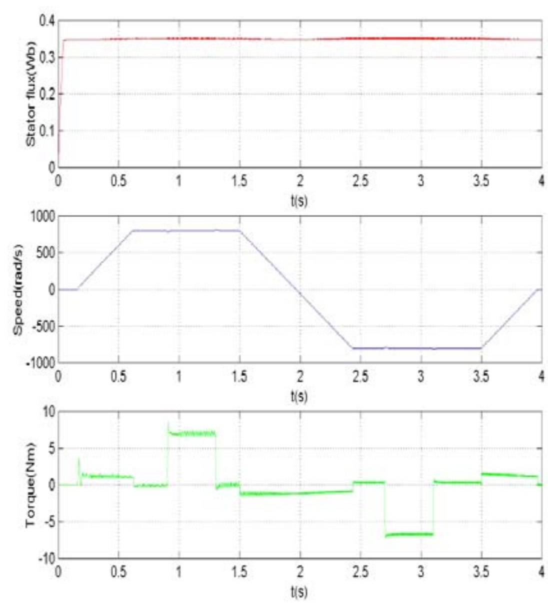

Figure 10 – Simulation: Results considering equation (35) for ONFC free parameter corrections

3.2.2 – Practical results

This item presents the results obtained from practical implementations of the vector control strategy FOVS, using simply equation (35) for the ONFC free parameter corrections of the speed controller. The stator flux is obtained from the method developed in [2, 4], where this flux is estimated from the stator equations with dc offset compensation. The parameter estimation is obtained from the automatic identification process presented in [3, 4]. Moreover, in order to validate the results obtained for the ONFC, the results obtained for the FOVS using PI controllers in the same test conditions, are also presented.

The figures 11 and 12 present the stator flux amplitude, the speed and the load torque for practical implementations of the FOVS using PI controllers and the ONFC, respectively. These test include speed reversion and load steps. The table 1 shows some index used to compare the proposed controller performance in relation to the PI controller. The index *IQVD* represents the speed reduction when a load step is applied to the motor and is defined by equation (36), where $\Delta w_{r\ step}$ and $w_{r\ nominal}$ are the motor speed variation and its nominal speed, respectively. The index *TRD* represents the time spent for the control system become stable after a load step application. Finally, *ISE* is the *Integral of Square Error*

Table 1

Controller	*IQVD (%)*	*TRD (s)*	*ISE (rad/s)^2 x10^3*
PI	2,83	0,9	10,93
ONFC	3,65	0,3	5,87

$$IQVD(\%) = \frac{\Delta\omega_{r\ step}}{\omega_{r\ nominal}} 100\% \qquad (36)$$

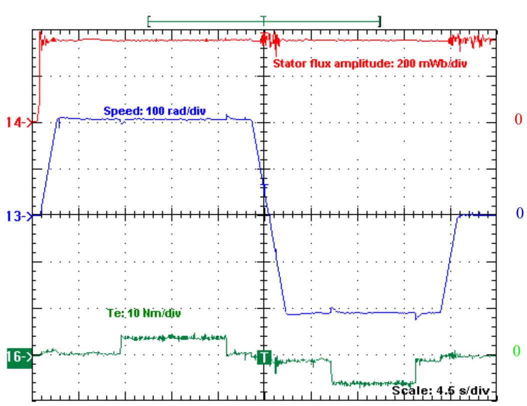

Figure 11 – Practical results for a 2 HP motor: FOVS using PI controllers with load steps

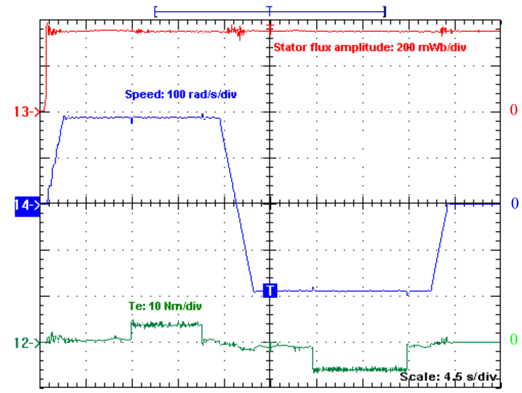

Figure 12 – Practical implementation: Results considering equation (35) for the ONFC free parameters correction of the speed controller

Like the simulations, the results from the ONFC show the good performance for the motor under control, even during transient conditions. Although the ONFC have presented a speed error a little beat greater than the error presented by the PI controller, the time spent for the motor speed to return to the set point, as well as the integral of the speed square error presented by the proposed controller, have been smaller than the PI controller.

4 - CONCLUSION

This work has presented a new online neurofuzzy controller applied to control systems. The ONFC (*Online Neurofuzzy Controller*) has in its structure only one input and one output, associated by two fuzzy rules, with two fixed and two free parameters. The parameters correction is performed through the gradient method and it is function of the process error, which also is used as controller input.

The proposed controller has been developed firstly for single loop control, and in the sequence, it has ben generalized for multi-loop control in cascade configuration. In order to keep the proposed controller simplicity, even in cascade configuration, the adjustment process of the free parameters has been simplified. The proposed controller performance in a single loop configuration has been evaluated through digital simulations for a plant with reverse characteristic. For the cascade configuration, the ONFC has been used for vector control of an induction motor through stator field orientation – FOVS. This control structure has been used to evaluate the ONFC performance in a practical implementation, using PI controllers as reference.

Finally, should be emphasizing that the results obtained, both from digital simulations and practical implementations highlight the good performance obtained from the ONFC in single and multi-loop control configurations.

Appendix A – Motor data

Table 2 – Data motor

	Motor 2 HP
V_n (V)	160
I_n (A)	8.5
R_s (Ω)	0.995
R_r (Ω)	0.696
L_{ls} (H)	0.00236
L_{lr} (H)	0.00352
L_m (H)	0.0456
J_m (kgm^2)	0.00655

Acknowledgements

The authors wish to thank Gerdau Açominas S.A., PICDT/CAPES, FAPEMIG and CNPQ for the support.

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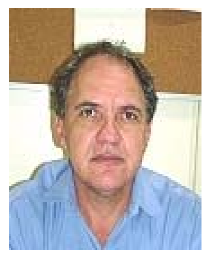
Marlon Rosa de Gouvêa was born in Belo Horizonte – Brazil, in 1965. He received the B. Eng. Degree in Electrical Engineering from Federal University of São João del Rei, in 1993, and the M. S. degree in Electrical Engineering from Federal University of Minas Gerais in 1995. He received the Dr. degree in Electrical Engineering from Federal University of Minas Gerais in 2005. Actually, He is the Steel Making Maintenance Manager of Gerdau Açominas, a steel manufacture company. His areas of interest are control of electrical drives and automation systems.

Eduardo Soares Figrueiredo was born in Governador Valadares – Brazil, in 1980. He received the B. Eng. Degree in Electrical Engineering from Federal University of Minas Gerais in 2004. Actually, He is engineer in the Industrial Technology Department of Gerdau Açominas, a steel manufacture company. His area of interest is automation systems.



Benjamim Rodrigues de Menezes received the B. Eng. Degree in Electrical Engineering from Federal University of Minas Gerais in 1977, and the M. S. degree in Electrical Engineering from COPPE - Federal University of Rio de Janeiro. In 1980 He received the Dr. degree in Electrical Engineering from Institute National Polytechnique de Lorranine, France, in 1991. Actually, He is Professor in the Department of Electronic Engineering, Federal University of Minas Gerais. His areas of interest are intelligent control and control of electrical drives.

Gustavo G. Parma received the B. Eng. Degree in Electrical Engineering from Federal University of Minas Gerais in 1996. He received the Dr. degree in Electrical Engineering from Federal University of Minas Gerais in 2000. Actually, He is Professor in the Department of Electronic Engineering, Federal University of Minas Gerais. His areas of interest are intelligent control and control of electrical drives.

Anderson V. Pires was born in Belo Horizonte – Brazil, in 1981. He received the B. Eng. Degree in Electrical Engineering from Federal University of Minas Gerais in 2004. Actually, He is engineer in ATAN. His area of interest is automation systems.

Walmir Matos Caminhas received the B. Eng. Degree in Electrical Engineering from Federal University of Minas Gerais in 1987, and the M. S. degree in Electrical Engineering from Federal University of Minas Gerais in 1989. He received the Dr. degree in Electrical Engineering from University of Campinas in 1997. Actually, He is Professor in the Department of Electrical Engineering, Federal University of Minas Gerais. His areas of interest are fail detection and diagnosis and computational intelligence.