Self tuning of output scaling factor for type-2 interval fuzzy controllers

Mouna Ghanai[1], Kheireddine Chafaa[1], Ali Medjghou[2], Nadia Bounouara[1]
[1]LAAAS Laboratory, Department of Electronics, Batna 2 University - Mostefa Benboulaid, Batna, Algeria
[2]LAAAS Laboratory, Department of Electronics, University Center of Tipaza, Tipaza, Algeria

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ABSTRACT

In this study presents a self-tuning type-2 fuzzy logic controller framework, which operates on the principle of continuously adjusting the controller structure by modifying the controller gain (scaling factor) as a function of the error and its rate of change, in order to achieve optimal control performance. The proposed structure is both simple and robust, with real-time gain adaptation facilitated by two type-2 fuzzy systems; the first one containing the rules of control task for speed regulation, and the second one containing the rules for the adaptation of the scaling factor. Both systems have the same inputs error and its variation. This work specifically focuses on tuning the output scaling factor, which is considered equivalent to the controller gain. The effectiveness of the proposed approach is evaluated through its application to the control of an induction machine, a system known for its complexity and strong nonlinearity. Simulation results demonstrate that the fuzzy controller significantly enhances performance, even under challenging operating conditions such as low-speed regimes.

Corresponding Author:

Mouna Ghanai
LAAAS Laboratory, Department of Electronics, Batna 2 University - Mostefa Benboulaid
Batna, Algeria
Email: m.ghanai@univ-batna2.dz

1. INTRODUCTION

In the last two decades, fuzzy logic controllers (FLCs) have been extensively used in the domain of control systems and control engineering, and it has been proven that they was successfully used for most of complex and nonlinear systems [1]-[4]. Fuzzy logic technique is used when want to obtain a control law without identify the plant under consideration, because in the other type of controllers, the plant under study must be identified before constructing the control law. It has been proven that FLCs are robust and their performances can be improved [5], [6]. Note that uncertainties can be handled by input (antecedent) membership functions, output (consequent) membership functions or even by linguistic rules. Type-1 fuzzy logic controllers (T1FLC) have the common problem that they cannot fully handle the linguistic and numerical uncertainties with an unknown uncertain, and perturbed nonlinear dynamical system as they use precise T1FLC. The uncertainty of a given unknown system causes problems in determining the exact and precise antecedents and consequents membership functions during the T1FLC design, and this can cause degradation in the T1FLC performance. This study proposes in this investigation to introduce type-2 fuzzy logic controllers (T2FLC) in order to overcome this drawback.

A type-2 fuzzy logic controller is a fuzzy system in which the membership functions of either the antecedent or consequent are type-2 fuzzy sets. These sets extend the concept of conventional fuzzy sets, also known as type-1 fuzzy sets. Unlike type-1 fuzzy sets, type-2 fuzzy sets have membership grades that are themselves fuzzy. A type-2 membership grade consists of a primary membership, which is any subset within [0, 1], and a secondary membership, also within [0, 1], that defines the range of possible values for the primary membership.

The performance of fuzzy logic controllers is highly dependent on the appropriate tuning of scaling factors, which act as interfaces between real-world variables and the fuzzy reasoning process. These factors determine how input signals—such as error and its rate of change—are mapped into the fuzzy domain, and how the resulting fuzzy outputs are translated into effective control actions. Poorly tuned scaling factors can significantly degrade system behavior, leading to slow responses, instability, or excessive control effort. While manual tuning offers a straightforward approach, it lacks adaptability and precision, especially in systems subject to dynamic or nonlinear changes. To overcome these limitations, various adaptive and optimization-based strategies have been introduced to automatically adjust scaling factors in real time. These methods aim to enhance the controller's ability to maintain stability and performance across a wide range of operating conditions, making the tuning and adaptation of scaling factors a critical component in the design of intelligent and robust fuzzy control systems.

To overcome this, several recent studies have considered this problem. The result in [7] employed a cascaded fuzzy controller for maximum power point tracking in a SEPIC–Luo converter connected to the grid. They emphasized precise tuning of input–output scaling factors to stabilize voltage and enhance tracking performance under varying solar irradiance and temperature conditions. Jouda *et al.* [8] propose a fuzzy logic controller optimized via particle swarm optimization to enhance maximum power point tracking in a boost-based photovoltaics (PV) system. The focus is on tuning scaling factors to improve speed, accuracy, and stability under varying irradiance and temperature. Simulation results validate the improved performance of the PSO-optimized controller. The study in [9] presents a battery energy management system for electric vehicles powered by a standalone PV source. An enhanced maximum power point tracking (MPPT) algorithm and dedicated controller based on adapted scaling factors. By appropriately setting these scaling factors, the fuzzy controller can make more accurate and responsive decisions for power flow. The study in [10] presents a methodology for enhancing the performance of a fuzzy power system stabilizer (PSS) by optimally tuning its input and output scaling factors using the bat algorithm. By integrating this nature-inspired metaheuristic optimization technique, the study aims to minimize system oscillations and improve damping performance under various operating conditions. The study in [11] introduces a fractional-order PID power system stabilizer whose parameters, including the crucial scaling factors, are optimally tuned using the bat algorithm. By adjusting these scaling factors alongside fractional gains, the controller achieves improved damping of low-frequency oscillations and enhanced dynamic response. The study in [12] proposed an interval type-2 fuzzy proportional integral derivative (PID) controller in which the input and output scaling factors are optimally tuned using a multi-objective optimization approach. The study demonstrates that proper adjustment of these scaling factors significantly enhances control accuracy and dynamic performance. The results confirm improved robustness and reduced error compared to conventional fuzzy-PID configurations.

In all cited works, optimization techniques are used to tune or adapt the scaling factors. In the present investigation, another approach based on type-2 fuzzy logic is proposed, in which two fuzzy systems are employed: (i) the first acts as a controller and (ii) the second, which represents the main contribution of this paper, functions as a tuner for the scaling factors.

In this paper, the authors propose a self-tuning type-2 fuzzy logic controller framework which is based on the fact that the controller always tries to manipulate the process input, usually by adjusting the controller gain (scaling factor) which is function of the error and change in error to get an optimal result. Its structure is simple and robust and the gain is adapted continuously using two fuzzy databases. This work concentrated on the adaptation of output scaling factor (SF), considering that it is the controller gain. The effectiveness of the proposed method will be tested on an induction machine control, which represents a complex and highly nonlinear system. Simulated results show that the proposed fuzzy controller is effective and significantly increases performances even in severe conditions (low speeds).

The rest of the paper is organized as follows: In section 2 induction mchine model is developed. The design approach of the suggested controller topology is discussed in section 3. The simulation and results discussions are provided in section 4. The conclusions are provided in section 5.

2. INDUCTION MACHINE MODEL

Because of their reliability, simple design, and lightweight construction, induction motor drives are increasingly being used as replacements for direct current motors, which suffer from several disadvantages such as sparking, corrosion, and the need for regular maintenance. Let's choose the state variable to be

$X = \left[I_{ds}, I_{qs}, \Phi_{dr}, \Phi_{qr}, \omega\right]^t$ (stator current, rotor flux and rotor speed in *d-q* system) and control input $V = \left[V_{ds}, V_{qs}\right]^t$, the model of the induction machine (IM) can be expressed as in (1).

$$\begin{cases} \frac{dI_{ds}}{dt} = -(\frac{1}{\sigma T_s} + \frac{1-\sigma}{\sigma T_r})I_{ds} + \omega_s I_{qs} + \frac{1-\sigma}{\sigma L_m T_r}\Phi_{dr} + \frac{1-\sigma}{\sigma L_m}\omega\Phi_{qr} + \frac{1}{\sigma L_s}V_{ds} \\ \frac{dI_{qs}}{dt} = -\omega_s I_{ds} - (\frac{1}{\sigma T_s} + \frac{1-\sigma}{\sigma T_r})I_{qs} - \frac{1-\sigma}{\sigma L_m}\omega\Phi_{dr} + \frac{1-\sigma}{\sigma L_m T_r}\Phi_{qr} + \frac{1}{\sigma L_s}V_{qs} \\ \frac{d\Phi_{dr}}{dt} = \frac{L_m}{T_r}I_{ds} - \frac{1}{T_r}\Phi_{dr} + (\omega_s - \omega)\Phi_{qr} \\ \frac{d\Phi_{qr}}{dt} = \frac{L_m}{T_r}I_{qs} - (\omega_s - \omega)\Phi_{dr} - \frac{1}{T_r}\Phi_{qr} \\ \frac{d\omega}{dt} = \frac{p^2 L_m}{J L_r}\left(\Phi_{dr}I_{qs} - \Phi_{qr}I_{ds}\right) - \frac{f}{J}\omega - \frac{p}{J}T_r\, sgn(\omega) \end{cases} \quad (1)$$

Where I_{ds}, I_{qs} are the *d-q* axes for stator current components; V_{ds}, V_{qs} those of stator voltage components; Φ_{dr}, Φ_{qr} those of rotor flux components; ω is the electrical angular rotor speed; ω_s is the electrical angular frequency of the reference frame; $T_s = \frac{L_s}{R_s}$ is the stator time constant, with R_s is the stator resistance and L_s is the stator inductance; $T_r = \frac{L_r}{R_r}$ is the rotor time constant, where R_r is a rotor resistance and L_r is a rotor inductance; L_m is the mutual inductance; $\sigma = 1 - \frac{L_m^2}{L_s L_r}$ is the leakage coefficient factor; J is the moment of inertia of the motor; p is the number of pole pairs; T_r is the resistive torque (load torque); and f is the viscous friction coefficient.

The electromagnetic torque T created by the motor can be written in terms of stator currents and rotor fluxes. This is expressed in (2).

$$T = \frac{pL_m}{L_r}(I_{qs}\phi_{dr} - I_{ds}\phi_{qr}) \quad (2)$$

Due to its efficiency, vector control for regulating the speed of induction motor drives has gained significant recognition. This method leverages the simplicity and effectiveness of DC motor control principles to manage induction motors, potentially lowering costs, particularly when motor speed is estimated without the need for sensors. It is well-established that vector control enables the decoupling of torque and rotor flux, enhancing control precision [13]-[15]. In the rotor flux oriented vector, the rotor flux is oriented to the d axis, so that $\phi_{qr} = 0$, and kept at a constant rated value $\phi_{dr} = \phi_r$.

Under this vector control, the fourth equation in system (1) will give us the following electrical angular frequency of the reference frame *(d, q)*. This is expressed in (3).

$$\omega_s = \omega + \frac{L_m R_r I_{qs}}{L_r \phi_r} \quad (3)$$

The flux will be reduced to the following simple model (third equation in system (1)).

$$\frac{d\phi_r}{dt} = -\frac{\phi_r}{T_r} + \frac{L_m}{T_r}I_{ds} \quad (4)$$

The generated motor torque T defined in (2) is reduced to a linear relation function of the torque current component I_{qs}. This relationship is further expressed in (5).

$$T_e = \frac{pL_m\phi_r}{L_r}I_{qs} \quad (5)$$

3. PROPOSED CONTROL FRAMEWORK

In this investigation, a combination of vector control technique with a type-2 fuzzy controller is considered (see Figure 1). The type-2 fuzzy controller itself is constituted of two blocks, a type-2 fuzzy speed controller block and a type-2 fuzzy gain adaptation mechanism block as shown in Figure 2. The output incremental torque ΔT^* (output incremental control action) is multiplied by the gain $G_{\Delta T^*}$ which represents the controller gain, and by output scaling factor α. Note that in this study, the control gain $G_{\Delta T^*}$ is chosen to be equal 0.9.

The scaling factor α is adjusted one-line by another type-2 fuzzy logic system called gain adaptation mechanism (see Figure 2). Because the existence of this adaptation using the values of e and Δe, this control system will allow to give best performances to the output. It can be said here that the control action is adapted online based on the tuning of the output scaling factor which is the output of a type-2 fuzzy logic system.

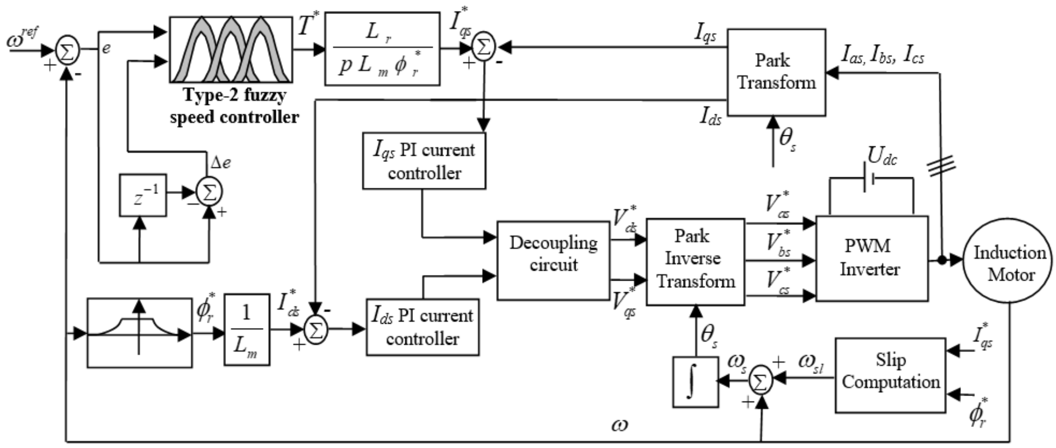


Figure 1. Block diagram of the proposed control framework

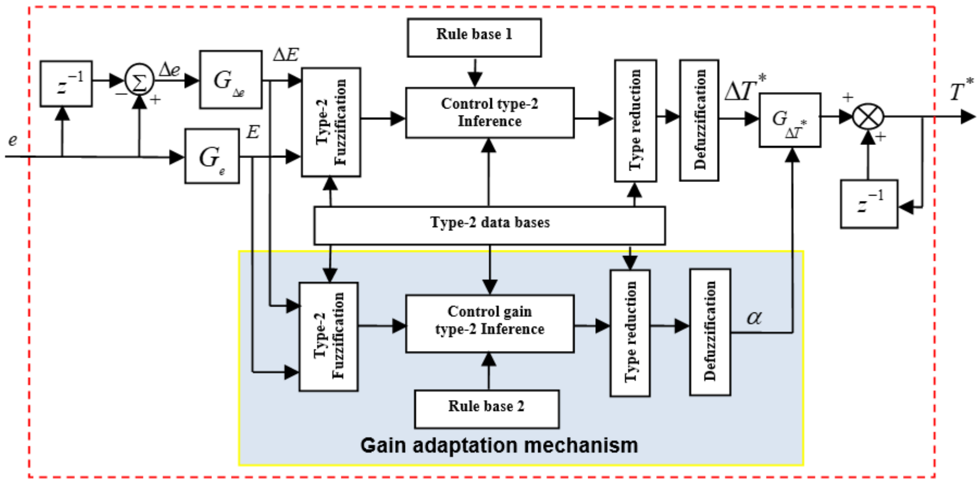


Figure 2. Internal structure of the type-2 fuzzy speed controller diagram of the proposed control framework

The error e is defined to be the difference between the input reference speed ω^{ref} and ω the actual electrical angular rotor speed, i.e. $e_k = \omega_k^{ref} - \omega_k$ where k represents the actual time instant (see Figure 1). The change in error Δe is defined to be variation in the error, which means the difference between the actual error e_k and the previous one e_{k-1}, i.e. $\Delta e_k = e_k - e_{k-1}$ as shown in Figure 2. Note that the actual value of the controller output T_k^* at time k is obtained by (6).

$$T_k^* = T_{k-1}^* + \alpha G_{\Delta T_k^*} \Delta T_k^* \tag{6}$$

Control law (6) is called a PI-type type-2 fuzzy logic control action. Our controller has two input variables (error e and change in error Δe) and one output variable ΔT^*. Values of e and Δe are normalized on the interval $[-1,1]$ by using input gains $G_e = 1/|\omega^{ref}|$ and $G_{\Delta e} = 1$, respectively (see Figure 3), and then type-2 membership functions of both e and Δe will be defined on $[-1,1]$ as shown in Figure 3(a). Membership functions of the incremental change in controller output ΔT^* are defined on the interval $[-10,10]$ (see Figure 3(b)), whereas the membership functions for the scaling factor α is defined on interval $[0,3]$ (see Figure 3(c)). This study use in this paper Gaussian type-2 membership functions for both variables e and Δe as shown in Figure 3, and interval membership functions for incremental control action ΔT^* and scaling factor α. Note that the interval membership functions of ΔT^* and α are considered as centroids of type-2 membership functions. The centroids are obtained from a type reducer mechanism which can allow transforming a type-2 membership function to a type-1 membership function.

Type reduction operation is the new part introduced in fuzzy logic systems; it concerns to transform type-2 fuzzy membership functions to type-1 fuzzy membership functions by using a specific algorithm called type reduction algorithm [16]-[18]. A type-2 fuzzy logic system shares a similar framework with a type-1 FLS, with the key distinction being that the antecedent and/or consequent sets in a type-2 FLS are of type-2. Consequently, each rule output set is also of type-2. The system consists of five main components: the fuzzifier, rule base, inference engine, type-reducer, and defuzzifier [19], [20]. The type-reducer plays a crucial role by performing a type-reduction operation, which extends the concept of type-1 defuzzification. This process transforms the type-2 rule output sets into a type-1 set, known as the type-reduced set. The type-reduced set is then subjected to defuzzification to produce a crisp output.

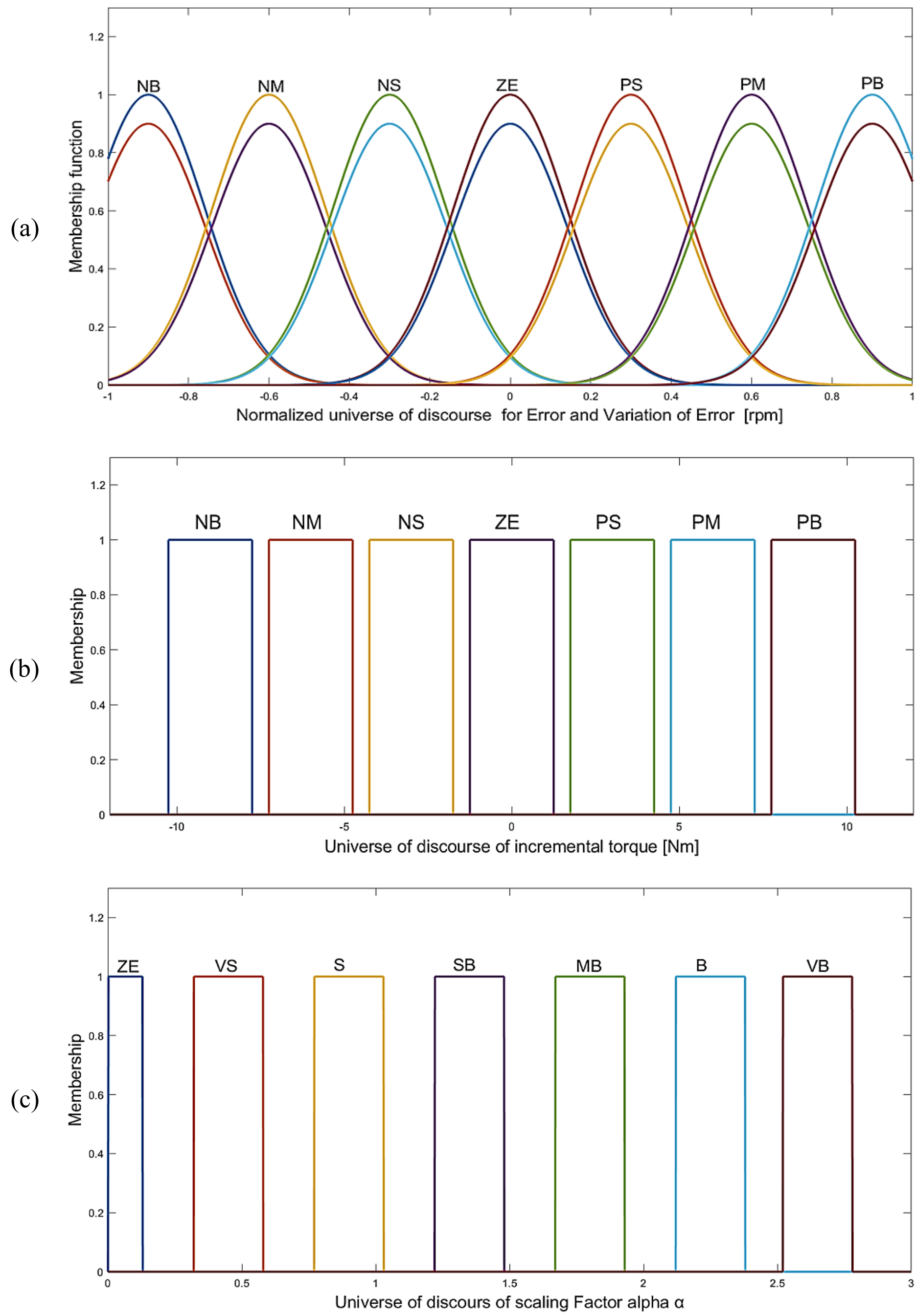


Figure 3. Membership functions of the control system: (a) error and its variation, (b) incremental torque, and (c) scaling factor

The combined process of type reduction and defuzzification is referred to as output processing as shown in Figure 4. The type-reduced set in a type-2 FLS captures the potential variations in the crisp output, which arise due to uncertainties present in the antecedents and/or consequents. Various methods of type-reduction exist [21]-[23]. In this paper, employed the center of sets type-reduction, which can be formulated as given in (7).

$$\Delta T 1^{M 1^{M}} \int_{\Delta T^1} \cdots \int_{\Delta T^M} \int_{w^1} \cdots \int_{w^M} 1 / \frac{\sum_{i=1}^{M} w^i \Delta T^i}{\sum_{i=1}^{M} w^i}_{l r_{cos}} \quad (7)$$

Where ΔT_{cos} is the control interval calculated by the interval endpoints ΔT_l for the left value and ΔT_r for the right value and $\Delta T^i \in [\Delta T_l^i, \Delta T_r^i]$ with ΔT^i the centroid of the type-2 interval consequent sets, and $w^i \in W^i = [\underline{w}^i, \bar{w}^i]$ the firing interval.

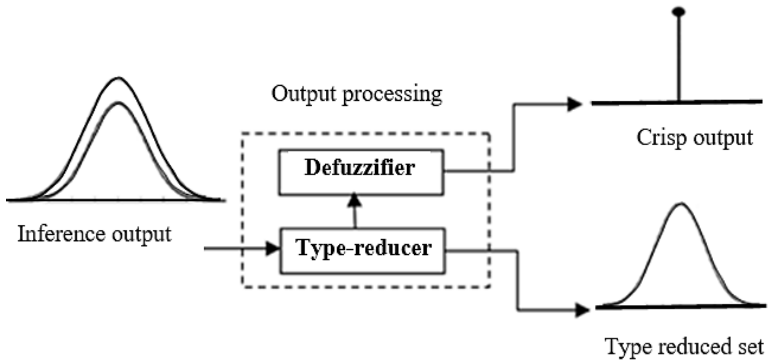


Figure 4. The structure of a type reducer, with its type-2 input and two outputs: the type-reduced set and the crisp defuzzified value

In type-2 fuzzy logic systems, type-reduction serves as an intermediate step between fuzzy inference and defuzzification, transforming the output type-2 fuzzy set into a type-1 fuzzy set. This process is essential for handling the additional uncertainty modeled by type-2 fuzzy sets. Among the various type-reduction methods, the Karnik–Mendel (KM) algorithm is the most widely adopted, particularly for interval type-2 fuzzy sets. Given N fired rules, where each rule i contributes a consequent $\Delta T_i \in R$ with an associated interval firing strength $w_i \in [\underline{w}_i, \bar{w}_i]$, the type-reduced set is defined by its centroid, expressed as an interval $[\Delta T_l, \Delta T_r]$. The left endpoint ΔT_l and right endpoint ΔT_r are computed using the following weighted average in (8).

$$\Delta T \frac{\sum_{i=1}^{N} w_i \Delta T_i}{\sum_{i=1}^{N} w_i}_{cos} \quad (8)$$

The KM algorithm begins by sorting the consequents y_i in ascending order and initializing all weights w_i to either their lower bounds (for ΔT_l) or upper bounds (for ΔT_r). The algorithm then iteratively adjusts the weights based on the position of the current estimate ΔT relative to the sorted ΔT_i values. Specifically, a switching index $k \in \{1,2,\ldots,N\}$ is identified such that:

for computing ΔT_l use : $w_i = \begin{cases} \underline{w}_i if i \le k \\ \bar{w}_i if i > k \end{cases}$, and for computing ΔT_r use $w_i = \begin{cases} \bar{w}_i if i \le k \\ \underline{w}_i if i > k \end{cases}$.

This process is repeated: for each iteration, the new ΔT is calculated using the updated weights, and the index k is updated accordingly until convergence is achieved (i.e., ΔT changes less than a predefined threshold). Once both endpoints ΔT_L and ΔT_R are computed, the type-reduced set is given as the interval $[\Delta T_l, \Delta T_r]$. Finally, defuzzification is performed by averaging the interval endpoints to obtain the crisp output $\Delta T^* = \frac{\Delta T_l^* + \Delta T_r^*}{2}$. The KM algorithm effectively captures the footprint of uncertainty inherent in type-2 fuzzy systems while maintaining computational efficiency suitable for real-time applications. Both stability analysis and KM algorithm details can be found in our previous work [1].

4. RESULTS AND DISCUSSION

To demonstrate the efficiency of the proposed controller, experimental simulations have been carried out. The control system which has been simulated is shown in Figures 1 and 2 with corresponding membership function of Figure 3 and using a PWM inverter. In this section, the induction motor and its controller are executed on a PC using MATLAB software (version R2022b) in order to prove the performance of the proposed method. Notice that our programs are written in MATLAB M-files with sampling period 10^{-4} sec. The used parameters of the machine are given in Table 1.

Table 1. Induction motor parameters (1.5 kW, 220/380 V, 50 Hz)

Parameter	Value
R_s	4.850 Ω
R_r	3.805 Ω
L_s	0.274 H
L_r	0.274 H
L_m	0.258 H
J	0.031 Kg m^2
f	0.080 N m s
p	4

The incremental change in controller output delivered by control type-2 inference (see Figure 2) is a type-2 fuzzy membership function, and let note it by $\mu_{\Delta\tilde{T}^*}$. The type reducer block in Figure 4 will then transform the T2MSF $\mu_{\Delta\tilde{T}^*}$ to an interval membership function represented by a center of set $\Delta T_{cos}^{*[T_l^*,T_r^*]}$ (7). To obtain a crisp output ΔT^* from the control interval ΔT_{cos}^* called also a type reduced set, it must defuzzify. Since this type reduced set is an interval set, therefore, the defuzzified output of ΔT^* will be the average of T_l^* and T_r^*.

In experimentations, and to realize realistic trials, the induction motor states and measurement have been both noised by Gaussian perturbations with zero mean and variances 10^{-4} and 10^{-2}, respectively. The speed response and the speed reference of 1000 rpm are depicted in Figure 5, which shows good performances in tracking. Figure 6 presents the corresponding torque control, and Figure 7 depicts the scaling factor (controller gain), which shows how this gain varies in order to maintain the best performance.

Two robustness tests are also released as shown in Figures 5, 6, and 7. Load charge and parameters variation: Applying a load charge of 20 N.m from t =0.5 s to t = 1 s. Then from t = 1 s to t = 1.5 s apply a parametric variation of 50 % for the rotor resistor and decrease all the inductances L_r, L_s, and L_m by 20 %. At time 1.5 s, and with this parameter perturbation, the same load charge is applied. Under these conditions, an excellent load charge rejection and insensitivity to parameter variation at times t = 0.5, 1, and 1.5 s are obtained, as depicted in the motor speed response in Figure 5. The corresponding electromagnetic torque response and scaling factor shown also in Figures 6 and 7 are generated to keep speed regulated and to compensate the load charge and parameters variation. To summarize, in Figure 7 can see how the adaptation of the scaling factor is changing during time, which increases the performances of the proposed controller and compensate all cited perturbations. Therefore, simulation results show that the speed response with the proposed technique yield excellent dynamic performances assuring insensitivity to the hard working conditions

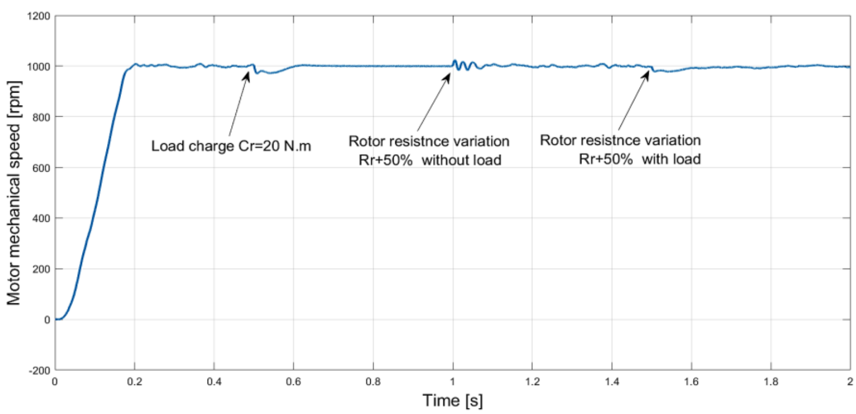


Figure 5. Speed response under robustness tests with load charge and parameters variation

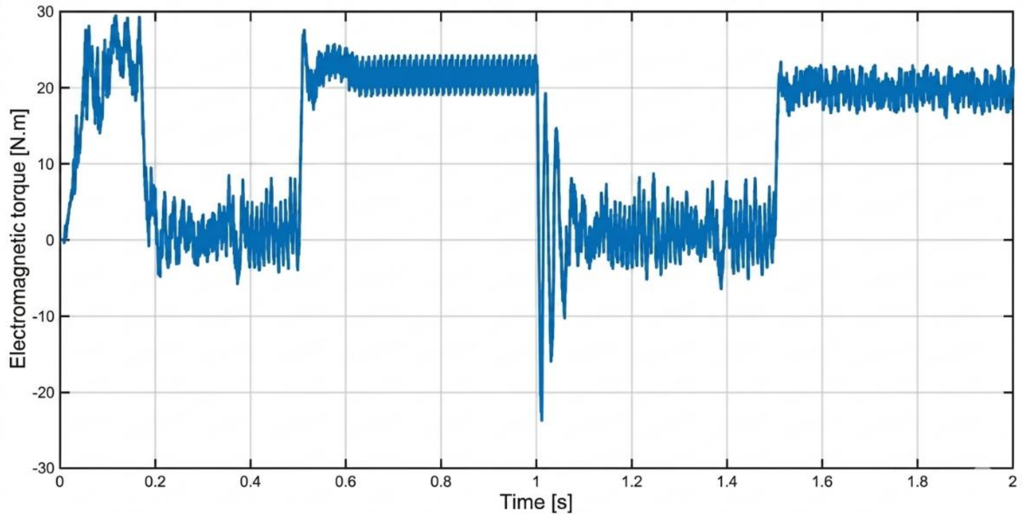


Figure 6. Generated control action (electromagnetic torque)

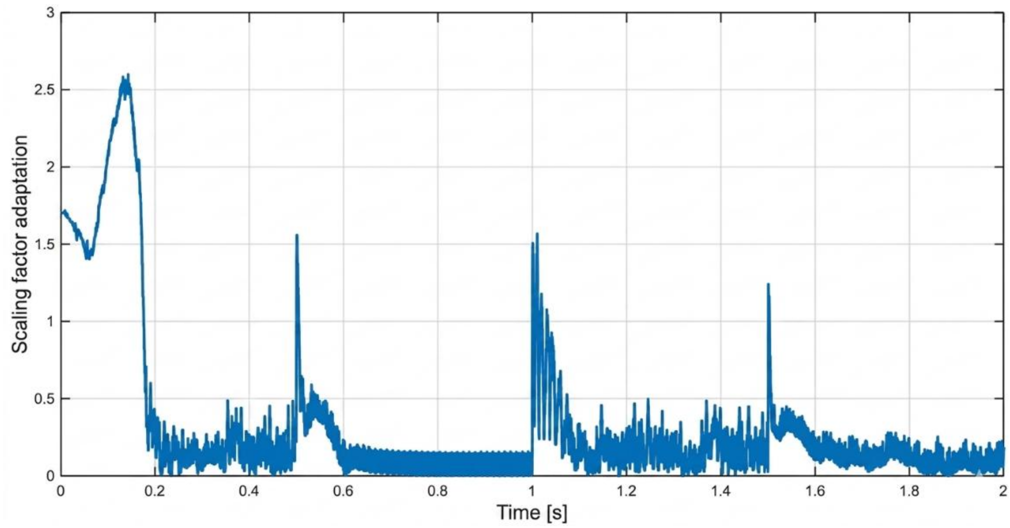


Figure 7. Generated scaling factor (adaptive gain)

To evaluate the performances of proposed approach, a comparision with an optimized PSO-PID controller and a non adapted type-2 fuzzy controller will be investigted. The parameters of the PID controller (K_p, K_d, and K_i) are obtained using PSO algorithm as described in references [13], [24], [25]. Through optimization process, PSO population is fixed to 20 particles and its coefficients w, c_1, and c_2 are fixed to 0.8, 1, and 1.5, respectively. The non adaptive type-2 fuzzy controller is obtained just as the adaptive type-2 fuzzy controller but without using the tuning mechanisme. It is noticed that the introduced type-2 fuzzy adaptive controller gives more accurate rotor speed compared to the PID and the non adaptive type-2 fuzzy controllers as shown in Figure 8.

For numerical evaluation purposes, the performance of the introduced method is evaluated using the mean square error (MSE) criterion using the reference speed N_{ref} and the real speed N. The corresponding expression is given in (10).

$$MSE_{Speed} = \frac{1}{K}\sum_{i=1}^{K}(N_i - N^{ref})^2 \quad (10)$$

Table 2 the *MSEs* of speed for the three investigated controllers where approve the advantage with respect to precision of the proposed controller over the PID and the untuned type-2 fuzzy controller.

Table 2. Comparative table of *MSEs*

Performance	PSO-PID	Non-adaptive type-2	Adaptive type-2
MSE_{Speed}	$8.5812.10^6$	$3.4827.10^6$	$5.1359.10^5$
MSE_{Torque}	$4.7189.10^6$	$4.0269.10^6$	$6.2236.10^5$
$MSE_{Low\ speed}$	$2.9537*10^4$	$1.0583*10^4$	$1.2781*10^3$

To evaluate the quantity of energy needed for each controller, lets introduce the *MSE* relative to the torque with respect to zero torque in (10). The (10) is used to quantity of the control energy. According to this equation it is observed in Table 2 that the minimum motor torque is obtained with the adaptive type-2 fuzzy controller, which confirm that the given controller achieves superior performances (MSE_{Speed}) with minimum energy (MSE_{Torque}).

$$MSE_{Torque} = \frac{1}{K}\sum_{i=1}^{K}(T_{ei} - 0)^2 = \frac{1}{K}\sum_{i=1}^{K} {T_{ei}}^2 \quad (10)$$

To check further the efficiency of the proposed algorithm under more complicated situation, let's check it with speed reversing and a very big challenge which is the low speed called also zero-speed tracking. In this case, a reference speed of 20 rpm is used and reversed at time t = 1 s. The obtained results for this case are depicted in Figures 9 and 10, in which it is clearly observed the high performance (small ripples and fast response) of the proposed type-2 fuzzy controller with self-tuning parameters. Quantitative comparison with PSO-PID and the simple type-2 fuzzy controllers is given in the last row of Table 2, where the efficiency of the introduced controller is consistently confirmed. Figures 9 and 10 also provide a visual comparison of the studied controllers at low speed, highlighting the superior performance of the adaptive type-2 fuzzy controller.

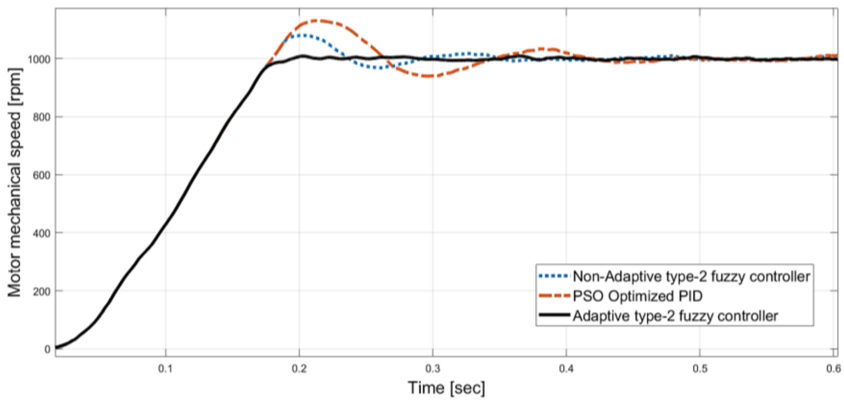


Figure 8. Superposition of the speed responses of PSO-optimized PID, simple type-2 fuzzy, and adaptive type-2 fuzzy controllers

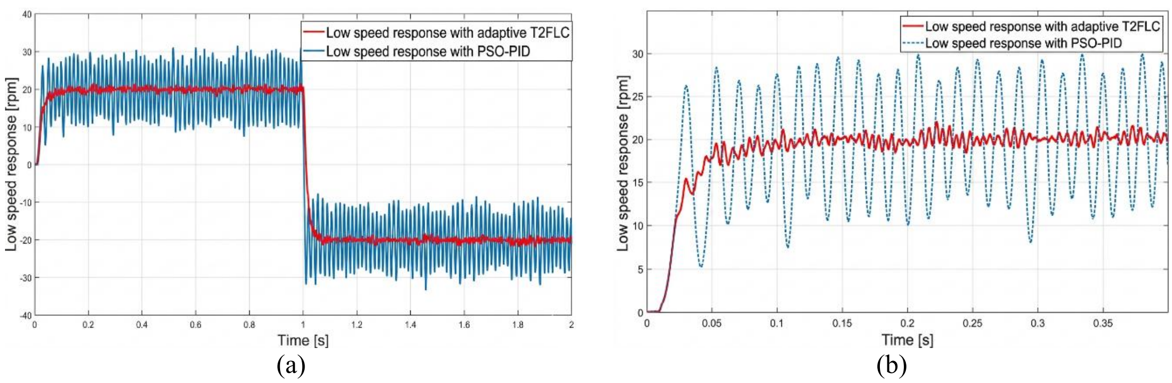
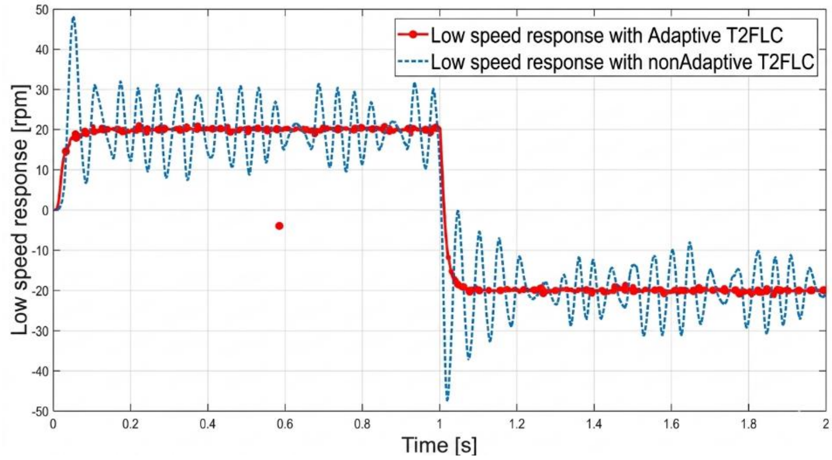
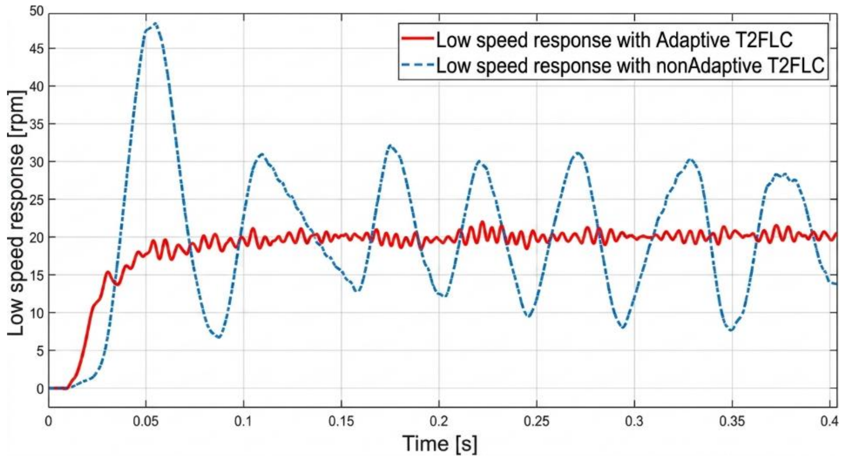


Figure 9. Robustness tests with low speed 20 rpm and direction reversing to -20 rpm at time t = 1 s: (a) 20 rpm responses of adaptive T2FLC and PSO-PID and (b) zoomed region in transient response of Figure 9(a)



(a)



(b)

Figure 10. Superposition of the speed responses in low speed case: (a) 20 rpm responses of adaptive T2FLC and non-adaptive T2FLC and (b) zoomed region in transient response of Figure 10(a)

5. CONCLUSION

In this paper presented a self-tuning type-2 fuzzy logic controller framework designed to dynamically adjust the output gain by continuously modifying the controller gain, represented as a function of error and change in error, to achieve optimal performance. The proposed framework is characterized by its simplicity, robustness, and reliance on two fuzzy databases for real-time output gain adjustment. The study focuses specifically on tuning the output scaling factor, and the effectiveness of the method is demonstrated through its application to the control of an induction machine a complex and highly nonlinear system. The proposed controller is basically constituted of two type-2 fuzzy systems; the first one containing the rules of control task for speed regulation, and the second one containing the rules for the adaptation of the scaling factor. Both systems have the same inputs error and its variation. Simulation results confirm that the proposed controller significantly enhances performance, even under challenging conditions such as load charge, parameter variation, speed inversion, and low speeds, underscoring its potential for practical implementation in demanding control scenarios.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Kheireddine Chafaa						✓		✓	✓		✓	✓		
Ali Medjghou	✓		✓	✓			✓			✓	✓		✓	
Nadia Bounouara	✓	✓		✓			✓		✓			✓		✓

C : **C**onceptualization
M : **M**ethodology
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Mouna Ghanai was born in Batna, Algeria, in 1975. She received the engineer degree in industrial control from Batna University, Algeria, in 1999, master degree in industrial control from Setif University, Algeria, in 2006, and the Doctorate Es-Science grade in electronic from Batna University, Algeria, in 2013. Currently, she is an assistant professor with the Department of Electronics, Faculty of Technology, University of Batna 2 Mostefa Benboulaid, Batna, Algeria. Her research interests include modelling and identification of nonlinear systems, automatic control, and biomedical signal processing. She can be contacted at email: m.ghanai@univ-batna2.dz.

Kheireddine Chafaa was born in Batna, Algeria, in 1971. He received the engineer, magister, and Doctorate Es-Secience diplomas in industrial control from Batna University, Algeria, in 1994, 1999, and 2006, respectively. Currently, he is a professor with the Department of Electronics, Faculty of Technology, University Mostefa Benboulaid, Batna 2, Algeria. His research interests include modeling and identification of nonlinear systems, nonlinear and adaptive control, soft computing, and biomedical signal processing. He can be contacted at email: k.chafaa@univ-batna2.dz.

Ali Medjghou received the bachelor degree in automatic, master degree in advanced automatic from Electrical Engineering Department, University of Biskra, Algeria, and doctorate degree in robotics and artificial intelligence from Electronics Department, University of Batna 2 Mostefa Benboulaid, Algeria. Currently, he is an assistant professor with the Department of Electronics, Institute of Science, University Center of Tipaza, Tipaza, Algeria. His research interests include robotic and artificial intelligence. He can be contacted at email: medjghou.ali@cu-tipaza.dz.

Nadia Bounouara was born in Batna, Algeria, in 1975. She received the engineer degree in control and magister degree in robotic from Electronics Department, Batna 2 University, Algeria, in 2001 and 2011, respectively. Currently, she is an assistant professor with the Department of Electronics, Faculty of Technology, University Batna 2 Mostefa Benboulaid, Batna, Algeria. Her research interests include nonlinear systems, type-1 fuzzy control, metaheuristic optimization, robotics and observers. She can be contacted at email: n.bounouara@univ-batna2.dz.