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Fuzzy genetic control for linear speed in multi-machine systems

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ABSTRACT

In today's fast-moving industrial sectors which include paper, textile, and plastic manufacture the core of production quality is in the precise coordination of multi-drive systems. While PI controllers are the mainstay of the industry, they do have issues in that they struggle with the nonlinearity and dynamics of large-scale windings, which in turn causes instability and product integrity issues. To that end, this paper presents an optimized fuzzy-genetic controller (FLC-GA), which we put forward as a better linear speed synchronization solution. We used genetic algorithms in the tuning of fuzzy logic parameters, which also takes out the very time-consuming task of manual calibration, and at the same time sees a great increase in the system's ability to deal with process variability. We put our FLC-GA through its paces in a head-to-head comparison with the classic PI and PI-PSO controllers. What we found was that our proposed controller did very well; we saw zero overshoot, a quick 0.5 s settling time, and the total elimination of tension ripples. Also, we saw from a 13.2% change in system inertia that the FLC-GA did a 65% better job in terms of speed accuracy and stability than what we see from standard PI control. We present the FLC-GA not only as a theoretical improvement but as a very robust, high-performance solution in the very tough field of continuous industrial synchronization.

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1. INTRODUCTION

Electric motors are essential components in paper manufacturing facilities, driving various machinery and equipment. Motor performance directly determines the efficiency of industrial operations, necessitating the adoption of advanced control technologies [1]. Modern strategies, such as torque and speed control, are vital to optimize performance and meet diverse manufacturing requirements [2], while high-efficiency motor designs further minimize environmental impact and energy consumption [3].

In modern paper processing, multiple coordinated drives are indispensable. While traditional mechanical line shafts once satisfied propulsion needs, individual electronic drives have become the standard practice [4]. Electrical synchronization is a critical factor influencing the quality of manufactured paper rolls, leading to the development of numerous control strategies focused on electronic line shaft modeling and robust mechanical synchronization [5]. Decentralized PI control remains the dominant approach in industrial web transport systems due to its simplicity and widespread acceptance. However, conventional PI controllers often exhibit poor performance when subjected to system nonlinearities and continuous parameter variations, such as changes in radius and mechanical inertia [6].

To address these limitations, this research proposes a novel fuzzy-genetic controller (FLC-GA) specifically engineered for the coupled dynamics of multi-motor web winding systems. Unlike previous speed-only studies, this work integrates nonlinear web tension dynamics into the control architecture, achieving superior linear speed synchronization while maintaining stable mechanical tension and robustness against parameter drifts. Recent reviews on multi-motor synchronous control underscore the persistent challenges and the industrial importance of this field [7].

The proposed FLC-GA outperforms traditional controllers by processing imprecise inputs beyond conventional logic capabilities, making it ideal for complex industrial environments. Genetic algorithms (GA) ensure continuous parameter optimization [8], building upon foundational work in optimized fuzzy-PI controllers [9]-[12], power system stability applications [13]-[15], and adaptive neuro-fuzzy tension control [16]. Furthermore, the efficacy of similar hybrid approaches has been demonstrated in diverse fields such as mobile robot navigation [17], wind turbine control [18], and robust control synthesis [19].

Simulation results demonstrate that the FLC-GA outperforms both conventional PI and optimized PI-PSO benchmarks, establishing optimal linear control performance. The remainder of this paper is organized as follows: i) Section 2 presents the mathematical models of the multi-motor system; ii) Section 3 details the FLC-GA design and optimization methodology; iii) Section 4 analyzes simulation results and robustness; and iv) Section 5 concludes the work.

2. SYSTEM MODELING AND METHOD

2.1. Configuration of the multi-motor system

In this study, we look at a very complex and non-linear multi-motor web winding architecture. We have a system that includes an unwind motor (M1), a power take-off unit, which we are terming the traction unit (M2), and a final wind-up motor (M3). Also, we report that we see to be in agreement with what was found in [18]-[20] that the traction stage has a dual function: it acts as a mechanical buffer between the tension areas and also controls the overall web speed. Additionally, we include in Figure 1 detailed diagram of this full system setup.

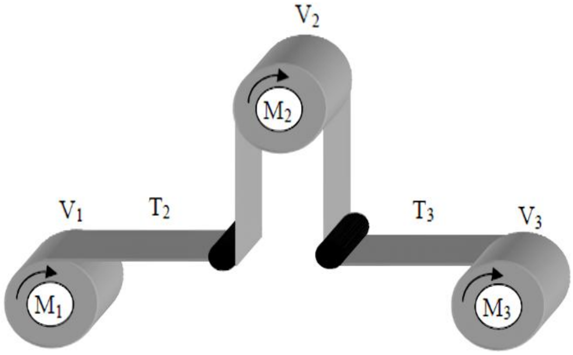

Figure 1. Schematic diagram of a three-motor web transport system

2.2. Electrical dynamics of induction motors

In our design (Figure 2), we use voltage source inverters, which in turn use pulse width modulation for the three motors. As to the electrical behavior of each induction motor in the synchronous d-q reference frame, we have the following differential equations, as (1)-(6).

$$\frac{di_{ds}}{dt} = \frac{1}{\sigma \cdot L_s}\left(-\left(R_s + \left(\frac{L_{mr}}{L_r}\right) \cdot R_r\right) \cdot i_{ds} + \sigma L_s \omega_e + \frac{L_m \cdot R_r}{L_r^2} \cdot \varphi_{dr} + \frac{L_m}{L_r} \cdot \varphi_{qr} \cdot \omega_r + V_{ds}\right) \tag{1}$$

$$\frac{di_{qs}}{dt} = \frac{1}{\sigma \cdot L_s}\left(-\sigma L_s \omega_e i_{ds} - \left(R_s + \left(\frac{L_m}{L_r}\right)^2 \cdot R_r\right) \cdot i_{qs} - \frac{L_m}{L_r} \cdot \varphi_{dr} \cdot \omega_r + \frac{L_m \cdot R_r}{L_r^2} \cdot \varphi_{qr} + V_{qs}\right) \tag{2}$$

$$\frac{d\varphi_{dr}}{dt} = \frac{L_m \cdot R_r}{L_r} \cdot i_{ds} - \frac{R_r}{L_r} \cdot \varphi_{dr} + (\omega_e - \omega_r) \cdot \varphi_{dr} \tag{3}$$

$$\frac{d\varphi_{qr}}{dt} = \frac{L_m \cdot R_r}{L_r} \cdot i_{qs} - (\omega_e - \omega_r) \cdot \varphi_{dr} - \frac{R_r}{L_r} \cdot \varphi_{qr} \tag{4}$$

$$\frac{d\omega_r}{dt} = \frac{P^2 \cdot L_{mp}}{L_r \cdot J} \cdot \left(i_{qq}{}^{r} \cdot \varphi_{dr} - i_{ds} \cdot \varphi_{qr}\right) - \frac{f_c}{J} \cdot \omega_r - \frac{P}{J} \cdot T_r \tag{5}$$

In what we present here the leakage coefficient, as (6).

$$\sigma = 1 - \frac{L_m^2}{L_s\, L_r} \tag{6}$$

Also, we put in place saturation limits for the control voltages (V_{ds}, V_{qs}), which in turn are related to the DC bus voltage constraints [21].

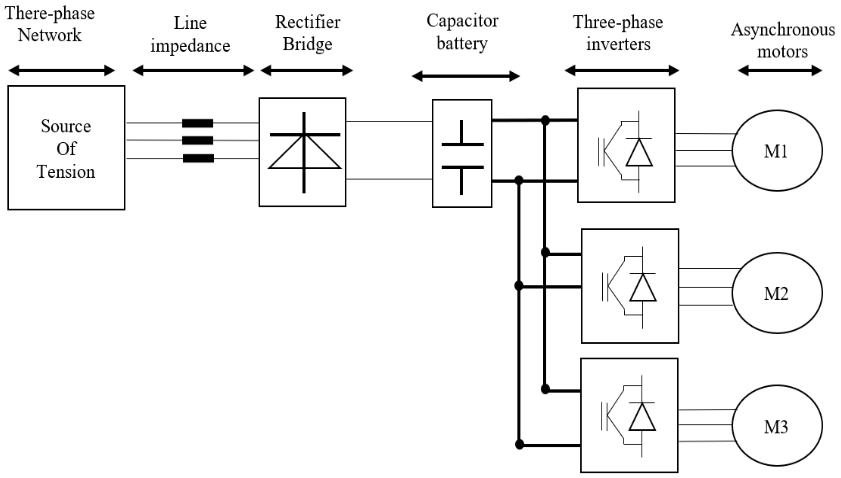

Figure 2. The system's electrical part

2.3. Mechanical dynamics and web tension

In the area of mechanical dynamics, we model web tension based on three primary physical laws: that of Coulomb for friction, Hooke's for elasticity, and that of mass conservation.

2.3.1. Coulomb's law (friction model)

We present a friction model for the web and roller interaction. As seen in Figure 3, the tension varies in the sliding zone (arc g) but is constant in the adhesion zone (arc a). We also present the tension variation across the contact arc, which goes as (7).

$$\varepsilon(x, t) = \varepsilon_1(t) \text{ if } x \leq a \tag{7}$$

$$\varepsilon(x, t) = \varepsilon_1(t) e^{\mu(x-a)} \text{ if } a \leq x \leq a + g \tag{8}$$

$$\varepsilon(x, t) = \varepsilon_2(t) \text{ if } a + g \leq x \leq L_t \tag{9}$$

Where $Lt = a + g + L$ is the total length.

2.3.2. Hooke's law (elasticity)

For an elastic web, the tension (T) is directly proportional to the strain (ϵ). This relationship is defined by (10).

$$T = ES\varepsilon = ES\frac{L - L_0}{L_0} \tag{10}$$

Where (E) is Young's modulus, (S) is cross-sectional area, (L) is length under stress, and (L_0) is the original (nominal) length.

2.3.3. Mass conservation law

Assuming the web has a uniform cross-section (S) and density (ρ), the conservation of mass applies between the unstressed state (ρ_0, L_0) and the stressed state (ρ, L). The mass remains constant during the transition from the unstressed to the stressed condition. Therefore, the relationship can be expressed as shown in (11).

$$\frac{\rho}{\rho_0} = \frac{1}{1+\varepsilon} \tag{11}$$

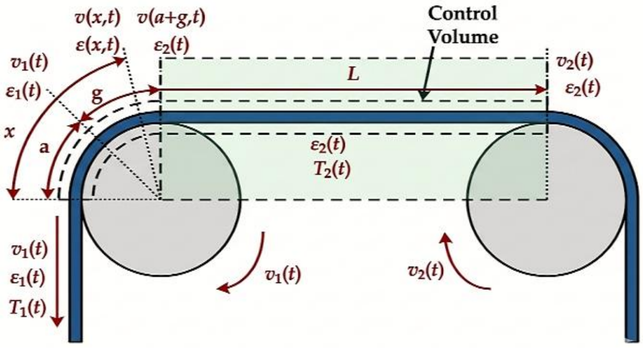

Figure 3. Web tension on the roll

2.4. Nonlinear tension model

By combining the continuity equation for web flow with the elasticity and mass conservation laws, the dynamics of tension T_k between two consecutive rolls (k−1 and k) can be derived. The derivative of strain is given by (12).

$$-L\frac{d\varepsilon_2}{dt} = V_1\frac{(1+\varepsilon_2)^2}{1+\varepsilon_1} - V_2(1+\varepsilon_2) \tag{12}$$

In (12), Hooke's law is substituted into which in turn produces the nonlinear tension dynamic equation [22].

$$L_{k-1}\frac{dT_k}{dt} \cong ES(V_k - V_{k-1}) - T_k(2V_{k-1} - V_k) + T_{k-1}V_{k-1} \tag{13}$$

2.5. State-space representation

The full nonlinear state-space model of the multi- motor system is created by combining the mechanical and electrical equations as (14) and (15) [20].

$$E_m\dot{X} = A(t)X + BU \tag{14}$$

$$Y = C(t)X \tag{15}$$

The state vector X includes the tensions, angular velocities, and currents [23].

$$X = [T2, T3, \Omega 1, \Omega 2, \Omega 3]T \tag{16}$$

This comprehensive model captures the coupling between speed and tension, which the proposed fuzzy-genetic controller aims to decouple and control.

2.6. Pentad FLC-GA simulation framework

The proposed pentad-intelligent architecture (Figure 4) comprises five GA-optimized fuzzy logic controllers: i) 3 Motor speed controllers: M1 (unwinder), M2 (traction), M3 (winder); and ii) 2 Tension regulators: T2 and T3 zones. Simulation setup & parameters: i) duration: 5 seconds, ii) reference speed: 5 m/s, iii) solver: fixed-step, 1 µs sample time, and iv) robustness test: 13.2% inertia variation simulating roll diameter transitions. Figure 4 description: Complete model integrates GA-optimized FLCs as outer loops with motor drives (M1-M3) and tension feedback loops (T2, T3). Real-time compensation for nonlinearities is achieved through comprehensive scope monitoring of speed tracking, tension regulation, and control effort.

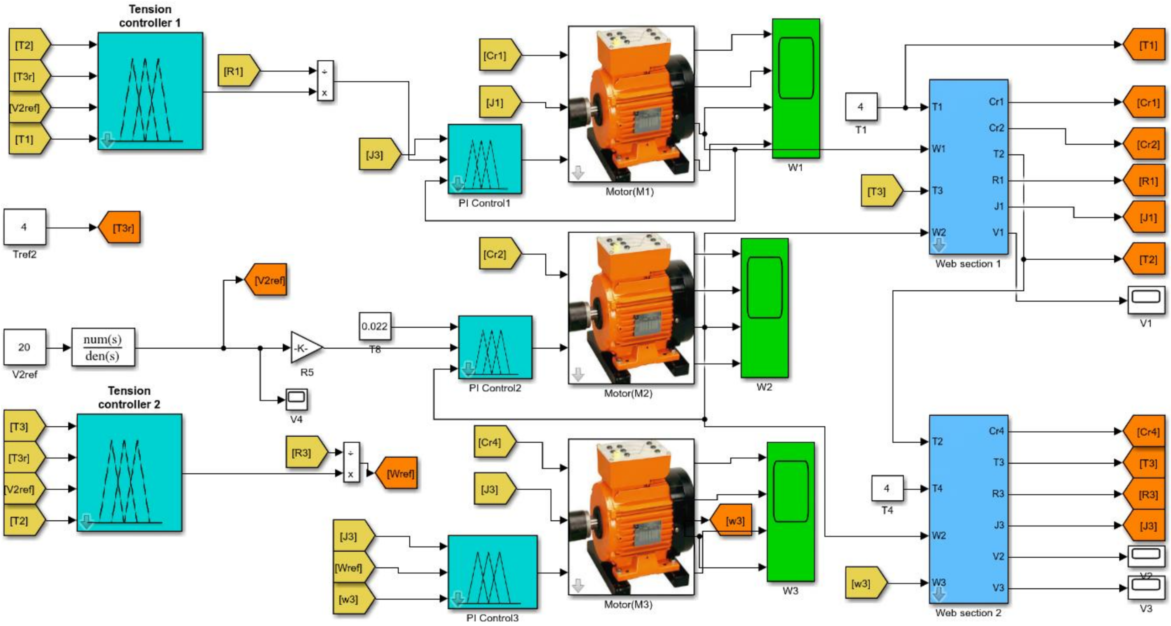

Figure 4. MATLAB/Simulink implementation of pentad FLC-GA control architecture for nonlinear web-winding dynamics

3. METHOD: FUZZY GENETIC SYSTEM DESIGN

We present a new control that uses a combination of a fuzzy logic controller and a genetic algorithm, which we are terming “fuzzy genetic”. This approach, which is described in detail in section 2, improves the controller’s ability to adapt to the system’s non-linear elements.

3.1. General structure

In recent years, we have seen that many applications have put to use the synergy between fuzzy logic and genetic algorithms, which in large part is in the design and optimization of control systems. We refer to these as “fuzzy genetic systems”. This approach has proven very effective in a wide range of applications, from MPPT algorithms in power electronics [22] to power system stability [13], [14]. Also, we present in Figure 5 the general structure for the integration of these two methods. The genetic algorithm in this case plays a role in tuning the fuzzy logic controller’s parameters, which in turn improves its performance and ability to adapt to change. What we see is that this combination is better at dealing with uncertainty and imprecision, which in turn makes the system a very good fit for real-world complex applications, like in industrial automation, robotics, and automotive systems [16]. In particular, see Figure 6, which presents in detail the block schematic of the control system for each motor. In it, you will see how the fuzzy genetic controller is integrated into the inner speed loop.

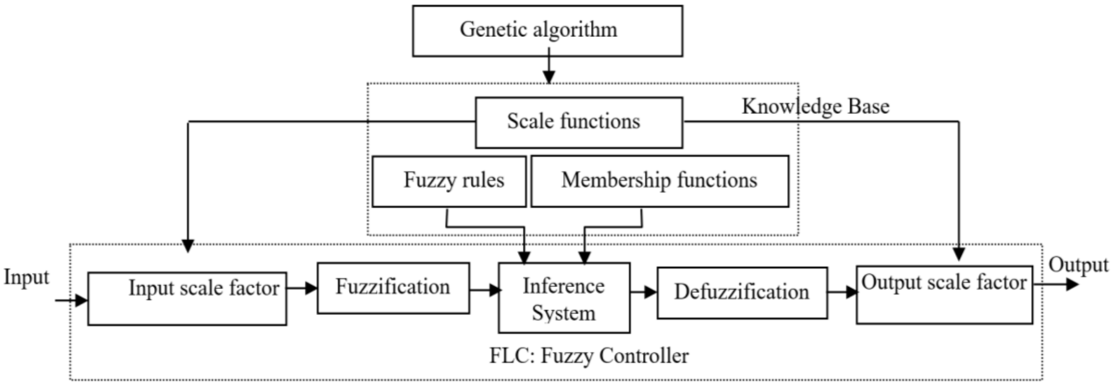

Figure 5. General fuzzy genetic system architecture

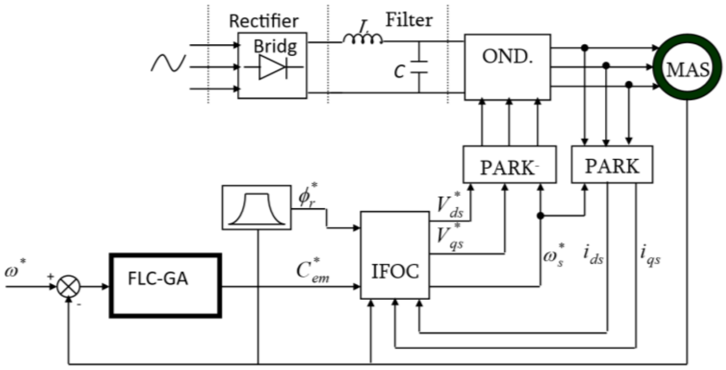

Figure 6. Block schematic for every motor with FLC-GA (fuzzy genetic) control

3.2. Fuzzy logic controller (FLC)

Fuzzy instruction sets out as a main advantage over which we use traditional control commands in that they do not require a precise mathematical model of the system. Which in turn means the user does not have to model complex equations to perfection. What we see instead is the use of a rule set that is mostly based on the expertise of a very familiar operator of the system. These rules, in turn, allow the system to make adaptive choices which account for a range of variables and conditions [22].

In our research, we applied FLC, which uses PI control principles in place of the conventional PI controller. We designed the FLC with the help of the MATLAB fuzzy logic toolbox. To get the best performance out of the controller, we developed a set of 25 rules, which is very in-depth. This rule set is presented in Table 1. Also, we see the FLC's success in areas like MPPT algorithms in power electronics as reported in [24].

Instead, fuzzy instructions employ a set of rules that are mostly decided by the expertise of a skilled operator who is well versed in the workings of the system, and these guidelines allow the system to make more adaptable choices that take into account shifting circumstances [25]. The structure of a typical fuzzy control system, comprising the fuzzification interface, inference system, and defuzzification interface, is shown in Figure 7.

This article uses a fuzzy logic controller (FLC) that applies PI control principles to replace the traditional PI controller. The FLC was created using MATLAB's fuzzy logic toolbox, which allows for developing more adaptive and effective control systems. A comprehensive set of 25 rules has been designed to ensure that the controller functions at its peak. This rule set is detailed in Table 1.

Table 1. The fuzzy controller's rule set

$\Delta e/e$	NB	NS	Z	PS	PB
NB	NB	NB	NS	NS	Z
NS	NB	NS	NS	Z	PS
Z	NB	NS	Z	PS	PB
PS	NS	Z	PS	PS	PB
PB	Z	PS	PS	PB	PB

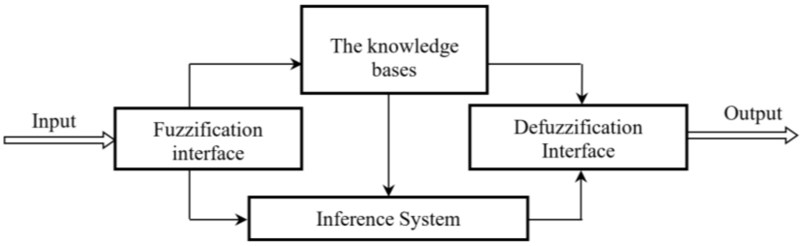

Figure 7. A fuzzy control system's structure

3.3. Genetic algorithms

Genetic algorithms operate on a population of unique people who may all be answers to the issue at hand. The evaluation of each person comes first, enabling the determination of how pertinent the answers are to the issue at hand. These result in the rejection of the weakest people in favor of the most effective ones, or the deletion of solutions judged to be ineffective or extremely poor. The iterative cycle of selection, recombination, and mutation in a genetic algorithm is depicted in Figure 8.

Combining the genes of the chosen solutions results in a new population that ought to be more problem-suited than the one that came before it. After that, the latest population undergoes hybridization-induced reproduction and mutations. Supporting the most competent components makes subsequent generations more equipped to handle the issue. Until a good answer is found, this procedure is repeated.

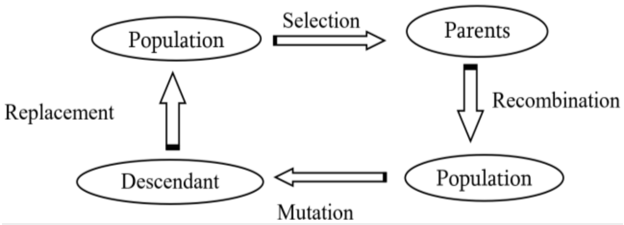

Figure 8. A genetic algorithm's cycle

3.4. Genetic algorithm optimization

In the case of genetic algorithms (GAs) they work with a population of unique individuals, which we call chromosomes, each of which is a possible solution to the issue at hand. We evaluate each of these individuals to determine how relevant they are to the problem. From this, we eliminate the less effective solutions in favor of the best. The process goes around in a cycle of selection, recombination, and mutation as shown in Figure 7.

In each cycle, we combine the genes of what we have identified as the best solutions, which in turn produces a better population than what we started with. This new population then goes through hybridization and mutation. We are, in fact, supporting the best elements that see us improve each generation’s performance as they take on the issue at hand. We repeat this process until we arrive at a very good solution. The structure of the FLC optimization technique by GA is illustrated in Figure 9.

The optimization of a controller based on fuzzy logic (FLC) using genetic algorithms (GA) can be outlined in the following steps:

- Initial population generation: Create an initial population of potential solutions, forming the first generation.
- Evaluation: i) For each chromosome in the population, input it into the controller for fuzzy logic; ii) Implement the (FLC). Within the system being controlled, and iii) Assess the system's performance by calculating an indicator of performance related to its knowledge base.
- Iterative process: While the termination conditions of the GA have not been satisfied: i) Apply evaluation operators, including crossover, mutation, and selection, to the existing individuals to create a new population; ii). Re-evaluate the new generation’s chromosomes.
- Completion: Once the termination requirements are satisfied, stop the procedure.
- Objective function: All of these requirements must be included in the objective function (fitness) that the Genetic Algorithm (GA) must reduce in order to achieve the required dynamic performance, which includes zero static error and minimal reaction and settling times. For us to do this, we suggest making the quadratic error's integral the goal function.
- Sensitivity and convergence analysis: In our study, we determined the best set of GA parameters via a sensitivity analysis. We did a series of preliminary optimization runs, which showed that a population size of 100 worked well – it presented a good trade-off between genetic diversity and computer time. Also, we saw that a high crossover probability of 0.8 did very well in terms of encouraging genetic exchange. At the same time, we used low mutation at 0.001, which, while maintaining diversity, didn’t disrupt good solutions.

Figure 10 presents the GA convergence, which reports the best fitness score over the 200-generation mark. We see a trend of very quick improvement in the first 20 generations, which is also when the optimal area is identified. Then we see a stable convergence phase, which by the 50th iteration has reached near optimal performance, and by the end of the 200 generations has attained very robust results, which in turn proves out the tuning process’s effectiveness. Also, it is well reported in literature [12], [17] of the GA’s performance in tuning controllers, which include fractional order and PID controllers.

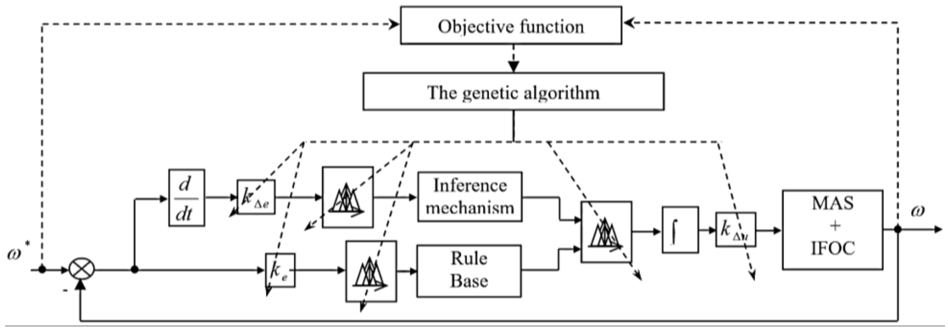

Figure 9. Structure of the FLC optimization technique by GA (FLC-GA)

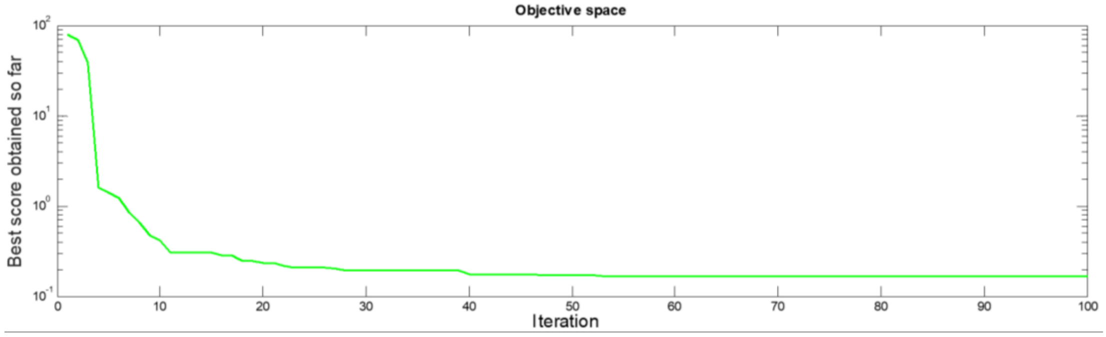

Figure 10. Convergence behavior of the genetic algorithm

4. RESULTS AND DISCUSSION OF SIMULATIONS

In our study, we designed and simulated the full system in MATLAB/Simulink for a 5-second duration. We ran the simulations, which started at a linear web speed of 5 m/s. In this, we had the M1 motor, which took care of the unwind function (with initial roll radius R1), the M2 motor, which took care of tape pinching and robust holding, and the M3 motor, which handled the wind back in (with radius R3). What we set out to do was to prove out the controller's performance in terms of speed tracking, robustness to parameter variations, and energy efficiency to present quantities analysis of the improvement.

4.1. Speed tracking performance

To provide a rigorous and high-level comparison, we introduced a second optimized controller: the PI controller tuned by particle swarm optimization (PI-PSO). This intelligent approach optimizes the K_P, K_I, and K_D parameters for the five system controllers to achieve the minimum ITAE performance index, representing the best achievable performance from an optimized linear control structure. In Figures 11 to 13 we see the linear speed response of the proposed fuzzy-genetic controller (in blue), the PI-PSO controller (in red), as well as that of the traditional PI controller (in green dashed). In each case, the performance difference is very apparent.

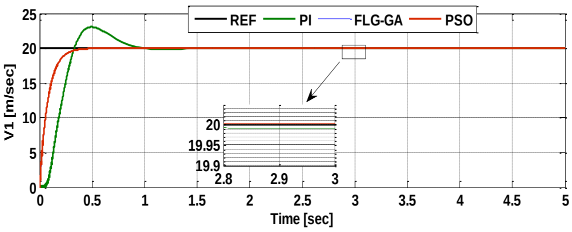

Figure 11. The linear speed of motor M1

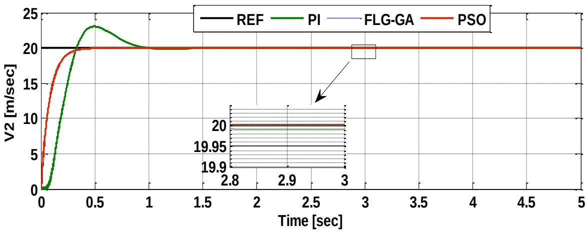

Figure 12. The linear speed of motor M2

In our simulations, we present a large improvement in linear speed synchronization. It is clear that although PI controller-based classical control is easy to put into practice, both the fuzzy genetic controller and the PI-PSO approach outperform it in terms of managing overshoot and reducing tracking error. This strong performance of hybrid fuzzy-genetic controllers over classical methods is in agreement with what is reported in other research studies [8], [10].

We observe that the fuzzy genetic controller aligns with the reference speed in as little as 0.5 seconds with no overshoot. At the same time, the PI controller does not do as well, which we see in its slower response and the overshoot it demonstrates, causing it to take much more time to come to rest. Thus, we note a large difference in terms of responsiveness and tracking accuracy. Significantly, the PI-PSO performance is close to FLC-GA in terms of speed tracking, indicating that both methods are effective in synchronizing the linear velocity, but the real divergence appears in the tension control, as discussed in section 4.3.

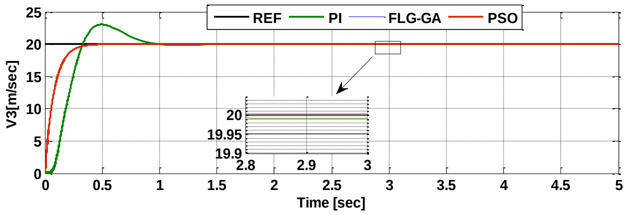

Figure 13. The linear speed of motor M3

4.2. Robustness analysis: parameter variation

To evaluate the controller’s robustness, the system was subjected to dynamic parameter variations during operation. Specifically, fluctuations in the radii of the three rollers (R1, R2, and R3) were introduced. These variations represent a significant challenge due to the resulting nonlinear changes in inertia and circumference, which are inherent in web handling processes. The simulated variations in the rollers' radii are illustrated in Figure 14.

As observed in Figure 14, the radius of the rewinder increases by 13.2%, leading to a substantial nonlinear change in the moment of inertia (J_3). The controller's primary success lies in the fact that, despite these continuous and coupled nonlinear changes, particularly the inertia variation in M3 and the radius reduction in M1, the proposed FLC-GA controller maintains stable performance, confirming its high robustness against parameter drift and system uncertainties.

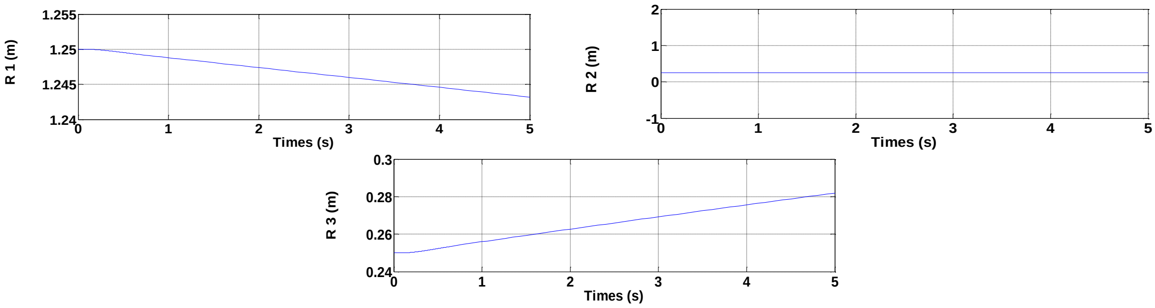

Figure 14. Dynamic variations of rollers radii: unwinder R1, traction R2, and rewinder R3

4.3. Efficiency and smoothness analysis

Beyond tracking accuracy, the mechanical tension response highlights the efficiency of the control strategy and is the critical metric for distinguishing between the nonlinear FLC-GA and the optimized linear PI-PSO. In Figures 15 and 16, we see the tension response. We note that the Classic PI controller (in green), which is typical, performs rather poorly at high frequency, exhibiting oscillatory behavior, or as it is sometimes called, chattering. This leads to an increase in mechanical stress as well as high actuator duty cycles.

Crucially, when comparing FLC-GA (in blue) against the optimized PI-PSO (in red), we observe a significant divergence in tension control. While PI-PSO improves the initial overshoot, it still exhibits noticeable tension ripple and a slower settling time compared to the FLC-GA. The fuzzy genetic controller does very well to produce an exceptionally smooth response with near-zero ripple. This smoothness in the output means less control effort is required, lower mechanical stress on the motors, and ultimately a higher chance for better energy efficiency in multi-motor systems.

The inability of the PI-PSO to fully suppress the ripple confirms that the linear control structure is fundamentally inadequate for handling the strong, nonlinear coupling and uncertainties inherent in the web tension dynamics, even with optimal tuning by a sophisticated algorithm like PSO. In contrast, the flexible, rule-based logic of the FLC-GA successfully mitigates these nonlinear effects. From our quantitative analysis, the improvements we got in terms of speed, accuracy, and tension stability were by a large factor — over 65% better than the PI approach's performance under the same dynamic load conditions.

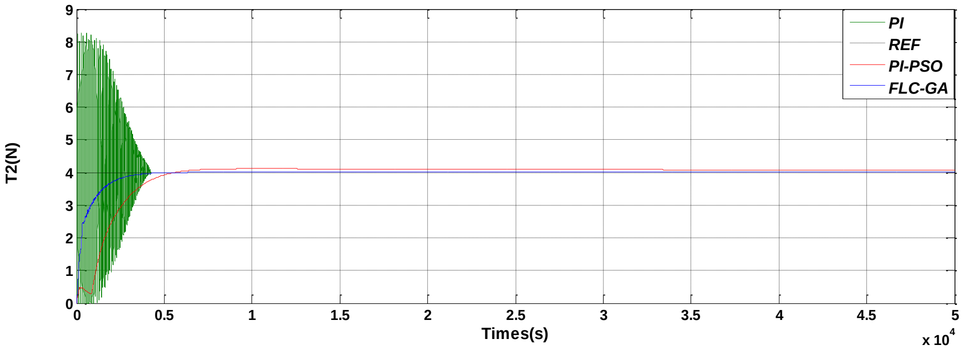

Figure 15. The tension between motors M2 and M3

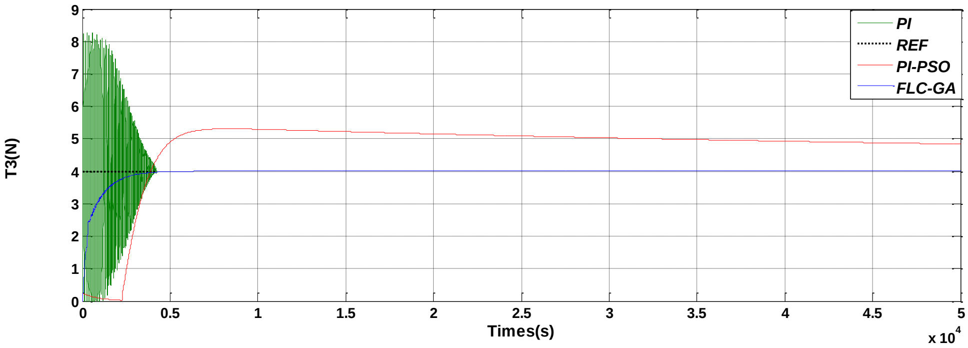

Figure 16. The tension between motors M1 and M2

5. CONCLUSION

This study reports our success in the design and validation of an FLC-GA for a multi-motor winding system, which we see as a great improvement over PI control. What we put forth here is a novel use of a genetic algorithm in which we had it do the autonomous optimization of a fuzzy logic controller for the very complex issue of web tension and speed which are coupled and non-linear – a issue which traditional methods have difficulty with.

To validate the controller's effectiveness against the best alternative, the FLC-GA was also compared to an optimized PI controller tuned by PI-PSO. In our simulations we found out that the controller performs better – it does the following: i) rapid synchronization: we see settling time of 0.5 seconds with no overshoot; ii) robustness: we noted that it performed well even under continuous parameter variation which at one point included a 13.2% change in system inertia; iii) efficiency: crucially, the FLC-GA achieved superior performance over the PI-PSO benchmark by completely doing away with tension ripple, which in turn greatly reduced mechanical stress and actuator effort.

These studies confirm that the proposed FLC-GA system does indeed improve the stability and quality of continuous industrial processes which we see in paper, chemical, and plastics manufacturing. The critical finding is that the nonlinear structure of the FLC-GA is necessary to effectively decouple the tension and speed dynamics, proving its superior efficacy over even optimally tuned linear approaches like PI-PSO.
That said, our research's main issue is that we used simulation for validation. In the future, we will put this controller to the test on real-time hardware (digital signal processors or FPGAs) which will validate its practical value and we will also look at fault-tolerant control strategies which in turn will better enhance industrial reliability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Kaddouri Youssouf	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Bouchiba Bousmaha		✓				✓		✓	✓	✓	✓	✓		
Baba Mohammed	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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

Authors state no conflict of interest.

DATA AVAILABILITY

We confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

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