

A New Approach for Intelligent Internal Model Controller Design Using the Genetic Algorithm

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ABSTRACT

This paper presents an advanced enhancement of the Internal Model Control (IMC) strategy by integrating a Genetic Algorithm (GA) to optimize the performance of robust control techniques applied to time-delay systems. Precise temperature regulation in electric furnaces is a critical requirement in various industrial sectors, including metallurgy, microelectronics, and chemical processing, where even minor deviations can significantly affect product quality, safety, and energy efficiency. However, conventional controllers, particularly classical PID regulators, often exhibit limited adaptability to parameter uncertainties, nonlinearities, and external disturbances, leading to degraded performance and potential instability. To overcome these limitations, an intelligent IMC-based controller is proposed, in which the inversion gain of the temperature regulation loop is optimally tuned (offline) using a Genetic Algorithm. The proposed approach ensures optimal tuning by employing multiple performance indices, including the Integral of Squared Error (ISE), Integral of Absolute Error (IAE), Integral of Time-weighted Absolute Error (ITAE), and Integral of Time-weighted Squared Error (ITSE), while also explicitly minimizing overshoot and improving transient response characteristics. Simulation results demonstrate that the optimized controller significantly enhances system stability, achieves zero overshoot, and improves robustness against external disturbances and abrupt setpoint variations. Moreover, the proposed method ensures accurate temperature tracking, faster settling time, and reduced energy consumption. These findings highlight the effectiveness of combining IMC with evolutionary optimization techniques and confirm its strong potential for improving control performance in industrial processes sensitive to time delays and thermal dynamics.

Keywords: Internal model control; genetic algorithm; stability; temperature control; electric furnace

INTRODUCTION

The main objective of robust control is to ensure the system's robustness against model imperfections, parametric uncertainties, and external disturbances that may occur (Saidi et al. 2023; Kinnari et al. 2023). Furthermore, it aims to improve stability, response time and accuracy when tracking specific trajectories (Abutaima et al. 2023).

Among the techniques for robust control of dynamic systems with potentially uncertain parameters, the strategy

of Internal Model Control (IMC) emerges. This control approach illuminates the path to addressing several inherent challenges despite uncertainties that may affect the model. One of its prominent advantages lies in its ability to ensure desired performance in the controlled system, such as stability, accuracy, and fast response (Touati et al. 2019; Saidi et al. 2021). The considered controller in the internal model control structure is selected as the inverse of the system model (Touati et al. 2019; Garcia et al. 1982).

Although several advanced feedback control strategies have been proposed in recent years, such as the

Gudermannian PID controller, softsign fractional-order controller, BELBIC-based PID controller, sigmoid PID controller, and neuroendocrine PID controller, these approaches often rely on nonlinear activation functions or bio-inspired mechanisms, introducing additional complexity in both design and real-time implementation. Moreover, they generally require a large number of tuning parameters and may involve high computational cost, which can limit their applicability in practical industrial systems (Suid et al. 2022; Ghazali et al. 2020; Ekinici et al. 2026). In contrast, IMC framework offers a structured and model-based design methodology with inherent robustness and straightforward implementation. One of its key advantages lies in its explicit use of the process model, which allows for systematic handling of uncertainties and disturbances while ensuring closed-loop stability (Garcia et al. 1982; Rivera et al. 1986). However, the performance of IMC strongly depends on the appropriate selection of its tuning parameters, particularly the inversion gain. Therefore, this work aims to enhance the IMC structure through an efficient optimization-based tuning strategy, providing a good trade-off between performance, robustness, and implementation simplicity.

The practical implementation of this approach poses challenges. It typically results in a structure that is generally infeasible for most physical systems. However, for certain classes of systems described by a transfer function with a numerator order equal to that of the denominator, and with stable zeros, the model inversion problem does not arise (Saidi et al. 2019). Unfortunately, these classes of systems are very limited, prompting us to extend studies to other physical systems such as those described by transfer functions with a numerator order lower than that of the denominator, systems with delays, and those with non-minimum phase features, as well as cases where the number of inputs differs from the number of outputs as for over-actuated or underactuated systems (Gilbert 2007; Yaman et al. 2017).

For these classes of systems where the model inversion is not feasible, various approaches have been suggested in the literature. One notable method was developed by Frank, which involves decomposing the system model into two sub-models in series. The first sub-model represents the part of the system potentially including unstable zeros and modelling delays of the model. The second sub-model contains the invertible and feasible model. This part is then used in practice to design the internal model controller (Frank 1974). The limitation of Frank's method for most physical systems is demonstrated in (Boimond et al. 1996). Indeed, this method does not consider the pure modelling delay and unstable zeros during the control calculation. Consequently, this can lead to a significant and persistent

deviation between the process output and the reference, especially during slow transient behaviours of the system.

Soudani et al. introduced a new method for the design of the internal model controller. This technique is based on a specific inversion, suitable for both single-variable and square multivariable systems, as described in (Touati et al. 2018). This approach has been adapted to allow model inversion in the context of continuous multivariable systems, whether over-actuated or underactuated, and whether linear or nonlinear (Touati et al. 2019; Saidi et al. 2021; Saidi et al. 2019; Dhahri et al. 2016; Mantri et al. 2013). In practice, this controller inversion involves the choice of an arbitrary inversion gain based on the class and type of studied system.

In recent years, several studies have focused on improving the performance of Internal Model Control through optimal tuning of controller parameters, particularly gain selection. Various optimization techniques have been proposed in the literature, including classical tuning rules and gradient-based methods, as well as advanced metaheuristic algorithms such as particle swarm optimization, genetic algorithms, differential evolution, and ant colony optimization (Kennedy et al. 1995; Holland 1992; Storn et al. 1997; Dorigo 1992). These approaches have been successfully applied to enhance robustness, disturbance rejection, and transient performance of control systems (Zhou et al. 2016). More specifically, some recent works have addressed the tuning of IMC parameters and filters to achieve improved closed-loop performance (Skogestad 2003; Tan et al. 2003). However, most of these studies are limited to specific classes of systems or focus primarily on filter design rather than the explicit optimization of the inversion gain within a generalized IMC framework. Moreover, their application to complex multivariable systems, including over-actuated and underactuated configurations, remains insufficiently explored. Therefore, there is still a need for a systematic and efficient optimization-based approach dedicated to inversion gain selection, which constitutes the main motivation of the present work.

The work presented in this paper focuses on our contribution, which involves selecting the optimal gain for the design of an internal model controller, thus ensuring stability and accuracy of the closed-loop system response. The use of a genetic algorithm is considered to evaluate the optimal value of the gain to be used in the inversion task, which will minimize the selected fitness function over time. Once the optimal gain is calculated, it is integrated into the regulation process. The main objective of the genetic algorithm is to minimize the fitness function to calculate the optimal gain which ensures an improvement in performance compared to the arbitrary gains.

BRIEF REVIEW OF IMC BASIC PRINCIPLE RTICIPANTS

In 1982, Garcia and Morari introduced the concept of Internal Model Control (Garcia et al. 1982). The IMC structure was specifically developed to design and implement the regulation of stable open-loop systems. The fundamental principle of IMC is based on the idea of tracking and reproducing an internal model that reflects the dynamic behavior of the system to be controlled. The goal is to minimize the difference between the output of the internal model and the actual output of the system by adjusting the controls appropriately. The controller acquires the characteristics of the system and adapts the controls accordingly to achieve the desired performance.

The basic configuration of the IMC, depicted in Figure 1, incorporates various components. $G(s)$ represents the transfer function of the process to be controlled, while $M(s)$ represents the explicit model of this process. $C(s)$ is the stable controller obtained by inverting the model $M(s)$. In this structure, an ideal control performance can be achieved with accurate modeling. Therefore, one of the main challenges within the IMC is to define the most appropriate model describing the physical process to be controlled.

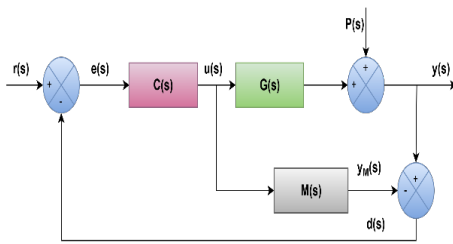


FIGURE 1. Generalized Structure of Internal Model Control

The control action u is simultaneously applied to the process $G(s)$ and its model $M(s)$. The difference between the outputs $y(s)$ of the process and $y_M(s)$ of the model, designated as d , is used to adjust the reference $r(s)$, to improve the control task of the process while considering disturbances, denoted as $P(s)$. One of the advantages of internal model control lies in its ability to handle disturbances and variations in the system. With an accurate internal model, the controller can anticipate the system's response to disturbances and adjust the controls accordingly to minimize undesirable effects. However, the IMC approach can be considered complex to implement as it requires an understanding of the internal model of the system. Additionally, if the internal model is not properly calibrated or if the real system exhibits unexpected behaviors, it can lead to performance issues for the controller.

The control signal $u(s)$ is expressed as a function of the reference r and the disturbance $P(s)$ as follows (Saidi et al. 2019):

$$u(s) = \frac{C(s)}{1+C(s)(G(s)-M(s))}r(s) - \frac{C(s)}{1+C(s)(G(s)-M(s))}P(s) \quad (1)$$

The relationship between the system output y and the reference parameters $r(s)$, as well as the disturbance $P(s)$, is defined by the following equation (Touati et al. 2019):

$$y(s) = \frac{C(s)G(s)}{1+C(s)(G(s)-M(s))}r(s) - \frac{1-C(s)M(s)}{1+C(s)(G(s)-M(s))}P(s) \quad (2)$$

This paper will adopt the internal model control structure, inspired by the work of Soudani et al. (Touati et al. 2019; Saidi et al. 2019). This control configuration ensures excellent performance in terms of stability, accuracy, and speed on the one hand. On the other hand, its simplicity lies in the ability to implement the controller $C(s)$ without the need for a filter for model inversion $M(s)$, thus obtaining the internal model controller. This control configuration is illustrated in Figure 2.

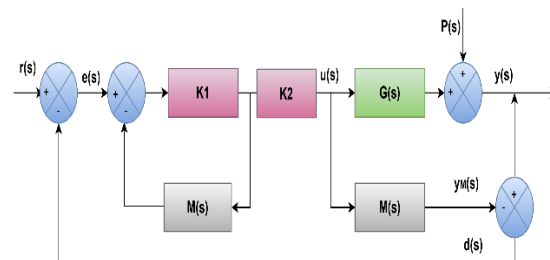


FIGURE 2. Internal model control proposed by (Soudani et al)

Referring to Figure 2, the following equation establishes the expression of the transfer function of the controller $C(s)$ for a specific category of systems

$$C(s) = \frac{K_1}{1+K_1M(s)} = \frac{1}{\frac{1}{K_1}+M(s)} \quad (3)$$

The expression for the gain K_1 is defined as follows:

$$K_1 = a, a \in \mathbb{R}^+ \quad (4)$$

The choice of the coefficient 'a' of the gain K_1 is crucial in the inverting task of the model. It is necessary to select significantly high value for the parameter 'a', as this choice is essential to ensure an effective approximation of the controller $C(s)$ that closely approaches the inverse of the model.

For certain systems, such as non-minimum phase systems and systems with delays, the required value of K_1 to ensure system stability may not be very high. Thus, for this class of systems, a gain K_2 is added to the internal model control structure, as illustrated in Figure 2. In fact, the use of gain K_2 aims to achieve zero steady-state error, ensuring perfect tracking of the system output with respect to its reference. For this specific system, introducing a high-value gain K_1 is delicate, as it could potentially induce system instability.

The formulation of the transfer function of the controller $C(s)$ for these systems is explained by the following equation (Touati et al. 2019):

$$C(s) = \frac{K_1}{1+K_1M(s)} K_2 \quad (5)$$

with the gain K_2 is described by the following equation (Touati et al. 2019):

$$K_2 = \frac{1+K_1M(0)}{K_1M(0)} \quad (6)$$

where $M(0)$ represents the static gain of the model $M(s)$.

PROPOSED CONTROL TECHNIQUE

The design of the internal model controller $C(s)$ is based on the approach of Soudani et al (Touati et al. 2019; Saidi et al. 2019). In practice, defining the optimal gain K_1 through conventional tuning techniques demonstrates complexity. This parameter K_1 holds crucial importance for inverting the model of the system $M(s)$ in the context of internal model controller design. To enhance the performance of the controller $C(s)$, the use of genetic algorithms (GA) is highly recommended. However, this combined approach with the inversion technique of equation (3) to find the controller $C(s)$ may be impractical for certain systems such as, minimum-phase and time-delay systems. To address this issue, the proposed idea involves using the inversion method presented in (Frank; 1974), which entails dividing the model $M(s)$ into two cascade sub-models defined by:

$$M(s) = M_+(s)M_-(s) \quad (7)$$

where $M_-(s)$ represents the part that admits an invertible and achievable model of $M(s)$.

$M_+(s)$ represents the part possibly containing unstable zeros and modeling delays of $M(s)$.

The equation below represents the proposed internal model controller in this context:

$$C(s) = \frac{K_1}{1+K_1M_-(s)} K_2 \quad (8)$$

The selected controller in this scenario corresponds to the inverse of the invertible and achievable part. Additionally, it enforces a unit gain on the transfer function $M_+(s)$ to ensure zero steady-state error between the process output y and the reference signal r . Consequently, the resulting controller has a static gain equivalent to the inverse of the model. A new internal model control structure, incorporating the use of genetic algorithm, is presented in Figure 3. The genetic algorithm was selected in this work to determine the inversion gain required for the internal model inversion process in the IMC design. This choice is motivated by its strong global optimization capability, robustness in handling nonlinear and non-convex problems, and independence from gradient information. Indeed, the inversion gain tuning problem is highly nonlinear and may present multiple local minima, making classical gradient-based approaches less reliable. GA provides an efficient global search mechanism that improves the likelihood of reaching an optimal or near-optimal solution for the model inversion task. Moreover, GA is flexible and easy to implement for different objective functions related to tracking performance and stability constraints. Compared to other AI-based optimization techniques, it offers a good compromise between convergence quality, computational effort, and implementation simplicity for the proposed IMC-based control design.

This approach aims to optimally adjust the gain K_1 of the internal model-based controller, by reducing the difference between the reference setpoint and the actual system output. Here, e represents the disparity between the desired output r and the actual output y , while u denotes the control law based on the internal model. The determination of this optimal gain K_1 will be carried out using a genetic algorithm.

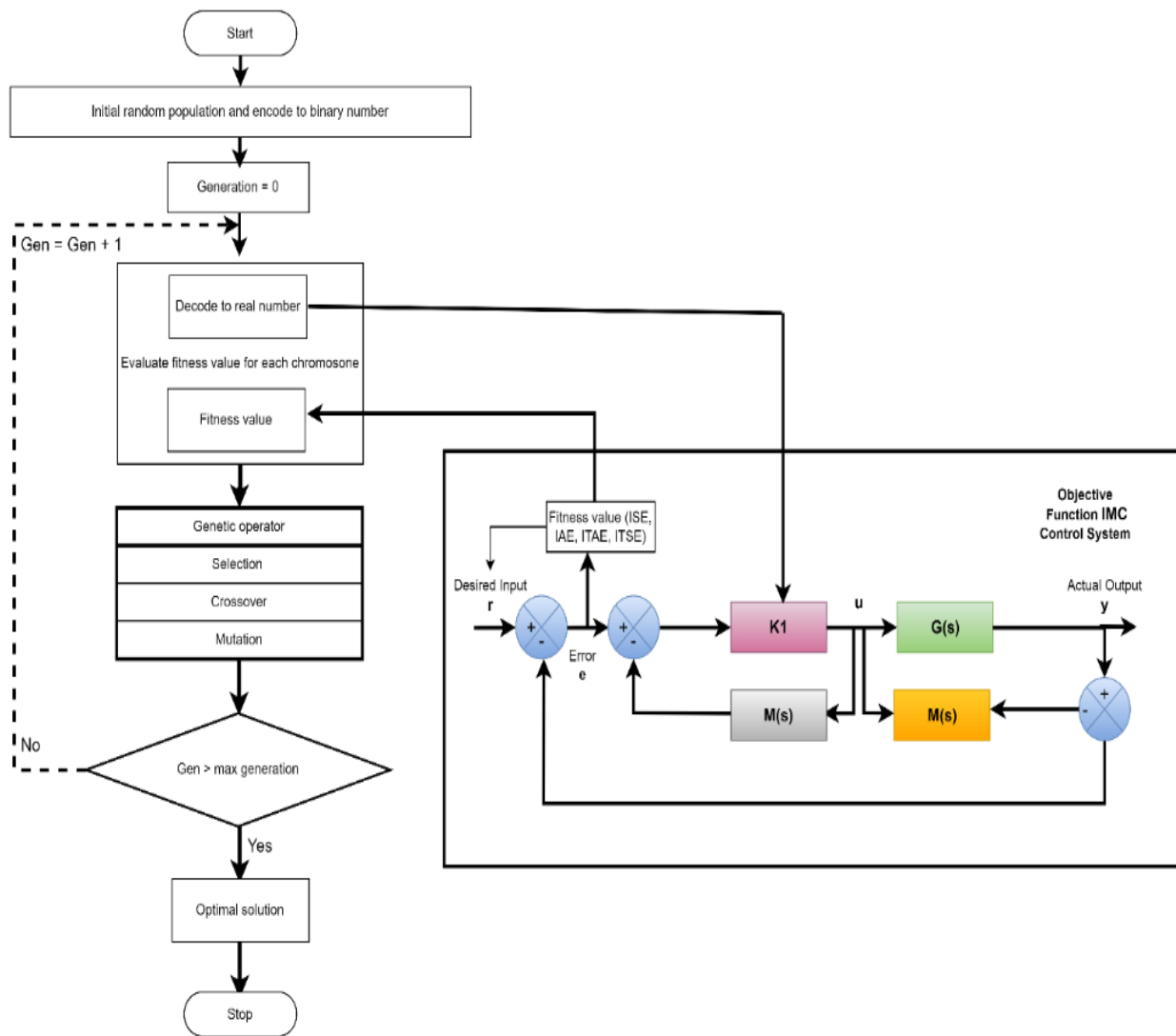


FIGURE 3. Flow chart of the internal model controller using genetic algorithm

The crucial steps of the genetic algorithm include (Man et al. 1996; Goldberg 1989; Che Mamat et al. 2022):

FITNESS FUNCTION

Four optimization criteria will serve as cost functions (fitness). These are commonly used error criteria, namely: integral of squared error (ISE), integral of absolute error (IAE), integral of time-weighted absolute error (ITAE), and integral of time-weighted squared error (ITSE). These criteria are formulated according to equations (Mantri et al. 2013).

$$ISE = \int_0^{\infty} e(t)^2 dt \quad (9)$$

$$IAE = \int_0^{\infty} |e(t)| dt \quad (10)$$

$$ITSE = \int_0^{\infty} t e(t)^2 dt \quad (11)$$

$$IAE = \int_0^{\infty} t |e(t)| dt \quad (12)$$

These classical performance indices primarily focus on reducing tracking error over time; however, they do not explicitly control transient characteristics such as overshoot. To further enhance the dynamic response of the system, an additional fitness formulation is introduced in this work, specifically designed for overshoot minimization (fitness function: overshoot minimization). The overshoot represents the maximum deviation of the system output from its steady-state value during the transient response. Accordingly, the fitness function is defined as follows:

$$F = \max(y(t)) - y_{ss} \quad (13)$$

where $y(t)$ denotes the system output and y_{ss} represents its steady-state value. The minimization of this objective function using the optimization algorithm reduces the peak deviation, leading to a smoother transient response and improved stability characteristics.

SELECTION

The selection phase in a genetic algorithm has crucial importance in the statistical identification of the most successful individuals in a population. It performs positive discrimination in favor of the best individuals, thus promoting their persistence and gradually eliminating less competitive individuals. This approach draws inspiration from mechanisms of natural selection by contributing to enhancing the overall quality of the population over generations.

CROSSOVER

During the crossover step of the genetic algorithm, two chromosomes interact by exchanging information, thereby generating new chromosomes known as offspring. These offspring selectively inherit certain characteristics from their parents, promoting genetic diversification and the creation of descendants with a unique combination of traits from previous generations (Mantri et al. 2013).

MUTATION

After the crossover step, the pre-selected individuals, whether derived from parents or offspring, undergo a mutation phase evaluated by a defined probability. Conventional mutation occurs by randomly selecting a gene within the chromosome and changing its value, introducing a localized variation in the genetic sequence (Mantri et al. 2013).

According to Figure 3, the goal is to explore the stability region to decide on the optimal parameter K_1 . This is achieved by a selecting technique based on the optimization criterion J , as defined in the genetic algorithm described below (Abachizadeh et al. 2010):

$$J = \begin{cases} ISE = \sum_0^{t_{max}} e(t)^2 \\ IAE = \sum_0^{t_{max}} |e(t)| \\ ITAE = \sum_0^{t_{max}} t|e(t)| \\ ITSE = \sum_0^{t_{max}} te(t)^2 \end{cases} \quad (14)$$

RESULTS AND DISCUSSION

The electric furnace, a sophisticated system encompassing a furnace, controller, temperature sensor, power regulator, and heating coil, represents a technological marvel in thermal management Figure 4. Within this intricate setup, the temperature is meticulously sensed by a high-precision sensor, which, in turn, produces a voltage signal. This voltage operates as a crucial negative feedback mechanism, intricately linked to the desired input temperature. The controller, a key component of this system, responds dynamically to the error voltage, to manage the regulation of the input power to the electric furnace. The proposed approach ensures not only accurate temperature control but also highlights the synergy among the various components in optimizing the electric furnace's performance (Paulusová et al. 2012; Sinlapakun et al. 2015).

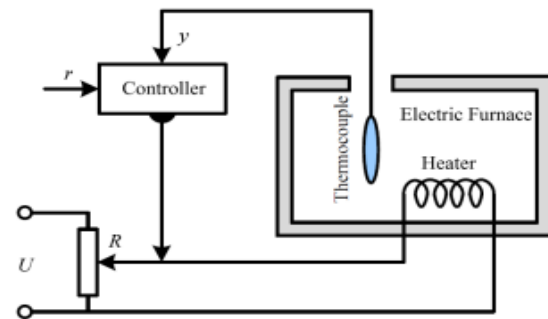


FIGURE 4. Diagram illustrating the control system for an electric furnace

The comprehension of various input responses and the enhancement of performance in the electric furnace hinge on the transfer function provided in reference (Gani et al. 2019). The mathematical representation of the furnace can be described as follows:

$$G(s) = \frac{0.15}{s^2 + 1.1s + 0.2} e^{-1.5s} \quad (15)$$

In this context, the proposed system is subjected to a constant temperature setpoint. Furthermore, our study system is controlled by an internal model controller based on genetic algorithms. Initially, the fitness function is defined using performance criteria such as ISE, IAE, ITAE, and ITSE. Subsequently, the fitness function is modified to prioritize overshoot minimization.

The simulations were carried out using MATLAB R2022a with a total simulation time of 30 seconds. The genetic algorithm was implemented using the MATLAB built-in optimization toolbox. To ensure reproducibility and a fair performance evaluation, the main GA parameters

were explicitly defined. The population size was set to 50 individuals, the maximum number of generations was fixed at 100, the crossover probability was set to 0.8, and the mutation rate was set to 0.1. These parameters were selected as a compromise between exploration capability and convergence speed. The stopping criterion was based on reaching the maximum number of generations or when no significant improvement in the objective function was observed.

A comparative study is then conducted to conclude the optimal fitness function for our work. Based on this choice, we will proceed with a study of the robustness of the internal model control.

INTERNAL MODEL CONTROL USING GA WITH FITNESS FUNCTION: ISE, IAE, ITSE AND ITAE

In this scenario, a desired temperature value, with an amplitude of 1, is applied to the “Electric Furnace” system. Additionally, our system, equipped with an internal model controller using genetic algorithms, is compared to the controller based on the Soudani approach. Figure 5 illustrates the results of this case study. From this figure, it is evident that the genetic algorithm-based controller, using the IAE error criterion as the fitness function, provides good dynamic responses compared to other controllers (Soudani-IMC, GA-ISE-IMC, GA-ITSE-IMC and GA-ITAE-IMC), with minimal overshoot and a short settling time, but a significant rise time within the accepted range. Moreover, the system with IMC based on GA-ISE, GA-ITAE, and the Soudani approach exhibits mediocre startup dynamics during the first five seconds. The detailed comparison is listed in Table 1.

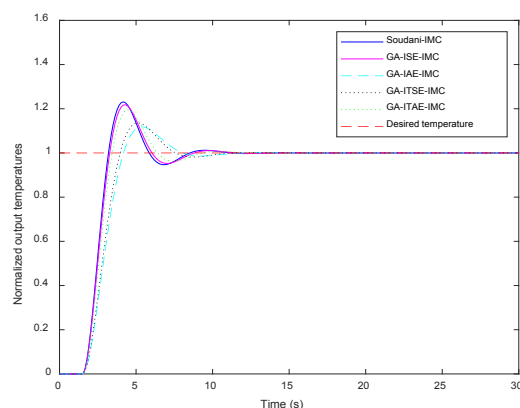


FIGURE 5. Comparative analyses of step dynamics responses in different methods GA-IMC

Performance parameters such as rise time, settling time and percentage of overshoot, are evaluated for the

internal model-based controller using the genetic algorithm, as presented in Table 1. It is evident from the results that the integral absolute error (IAE) yields better performance than other controllers.

TABLE 1. Comparison of the performance of the internal model controller using GA and performance indices

	Soudani	GA-ISE	GA-IAE	GA-ITSE	GA-ITAE
Rise time (s)	1.15	1.20	1.81	1.66	1.31
Settling time (s)	7.94	8.12	7.49	7.13	8.46
Overshoot (%)	23.10	21.80	11.78	13.66	19.52
K_1	10	9.31	5.05	5.71	8.16
K_2	1.13	1.14	1.26	1.23	1.16

Figure 6 illustrates the variations in control using an internal model with different fitness functions. Notably, the control based on the GA-IAE-IMC method exhibits an initial peak before stabilizing around the value of 1.6, indicating a more pronounced transient phase before reaching steady state.

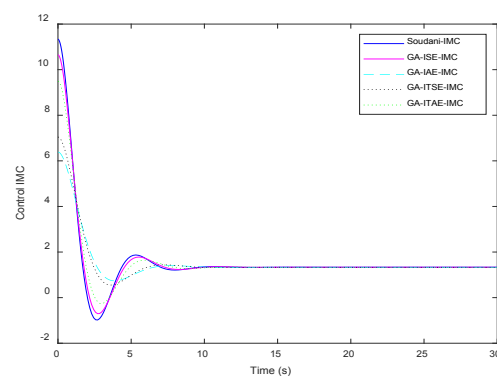


FIGURE 6. Evolutions of internal model control actions for four performance indices with the genetic algorithm

INTERNAL MODEL CONTROL USING GA WITH FITNESS FUNCTION: MINIMIZING OVERSHOOT

In this section, we implement an internal model controller optimized using a genetic algorithm, with a fitness function specifically designed to minimize overshoot (GA-OV-IMC). As illustrated in Figure 7, the controlled system demonstrates stable behavior, with its dynamic response exhibiting no overshoot and achieving zero steady-state error. Notably, the system’s response initiates after 1.5 seconds, attributed to the presence of a delay inherent in its mathematical model.

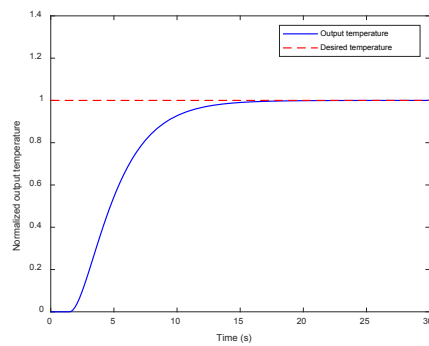


FIGURE 7. System response with the proposed GA-IMC having the fitness function: minimize overshoot

The system's performance is summarized in Table 2. We notice that the system responds more slowly compared to the scenario where fitness functions ISE, IAE, ITSE, and ITAE were considered. In fact, for our studied system, temperature overshoot can be severe and problematic during the use of the electric furnace in an industrial setting. Hence, we will consider this case when adopting this controller for our system.

TABLE 2. Comparison of the performance of the internal model controller using GA and minimizing overshoot

	GA-Overshoot
Rise time (s)	6.66
Settling time (s)	13.24
Overshoot (%)	0
K_1	0.55
K_2	3.42

Figure 8 shows the evolution of the internal model control using overshoot minimization as a fitness function. To eliminate undesirable temperature oscillations inside the electric furnace, the control exhibits lower energy than in the previous case. In fact, the amplitude of the control action reaches a value of 1.88 at the start and stabilizes around the value of 1.33. In this scenario, the system converges towards its reference value.

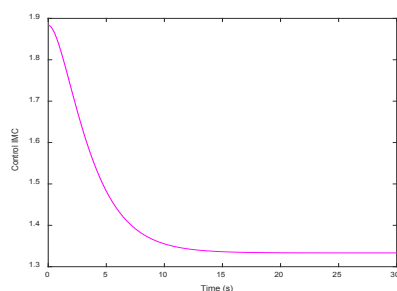


FIGURE 8. Temporal evolution of the internal model control

command

FIRST SCENARIO

In this scenario, we changed the setpoint at $t=30s$ with an amplitude of 1. Figure 9 presents the simulation results in this case. The dynamic responses of the temperature illustrated in this figure confirm the same observations obtained in the first scenario, where the internal model controller is highly effective in handling the change in the system input. The system output perfectly tracks its normalized desired temperature.

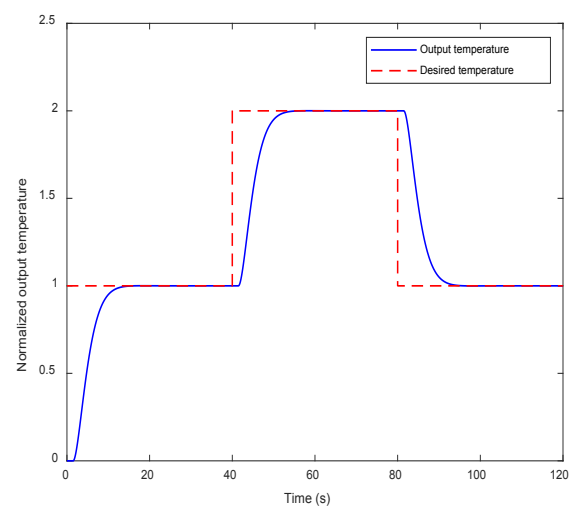


FIGURE 9. System response for input signal sequences

SECOND SCENARIO

In this context, we are studying the impact of a step load disturbance with an amplitude of 0.1 at $t=25s$. We are considering the optimal parameters $K_1=0.55$ and $K_2=3.42$, obtained using a genetic algorithm with a fitness function aiming to reduce overshoot. Figure 10 shows the dynamic response of the system to this disturbance. On the one hand, the system quickly eliminated the disturbance within 10 seconds and followed the reference setpoint with remarkable accuracy. On the other hand, the system demonstrates excellent performance in terms of settling time and zero overshoot.

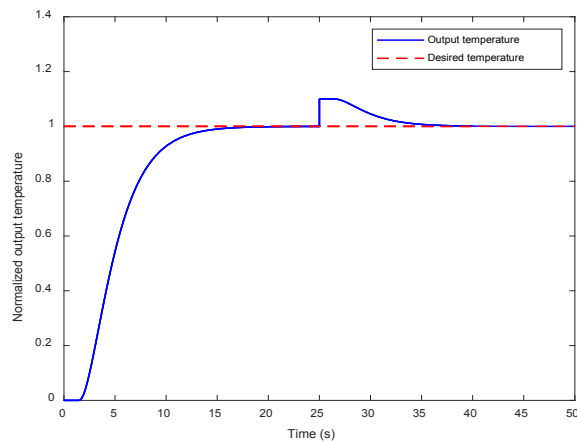


FIGURE 10. System response in the presence of disturbances

EVALUATION OF GA-OV-IMC VS PID AND FRANK-IMC

This section presents a comparative study to evaluate the performance of the proposed GA-OV-IMC control strategy. It is compared with Soudani's IMC-based method as well as two classical controllers implemented under identical conditions : a conventional PID and Frank's IMC approach. The comparison focuses on key performance criteria such as stability, response speed, overshoot, and robustness, in order to assess the advantages and limitations of each method and to provide a comprehensive evaluation of the proposed approach.

Before implementing the PID controller, its parameters were obtained using the direct IMC synthesis method, well suited for systems with pure time delay. The system studied, given by equation (15), is modeled as a first-order plus dead-time process with the following transfer function:

$$G(s) = \frac{K e^{-\tau s}}{Ts+1} \quad (16)$$

where K represents the process steady-state gain, T the time constant, and τ the pure time delay.

PID controller parameters are then obtained analytically according to the following relations :

$$K_p = \frac{T}{K(\tau + \lambda)}, T_i = T, T_d = \frac{\tau}{2} \quad (17)$$

where $\lambda > 0$ is a tuning parameter controlling the trade-off between response speed and robustness.

The equivalent PID controller gains are then computed as follows:

$$K_i = \frac{K_p}{T_i}, K_d = K_p T_d \quad (18)$$

The second Frank-IMC is based on Equation (7) and is expressed as follows :

$$C_{Frank}(s) = \frac{1}{M^-(s)} G_f(s) \quad (19)$$

where $G_f(s)$ is a filter introduced to ensure the practical implementation of the controller and must be chosen in a causal form.

$$G_f(s) = \frac{1}{(1+\tau_f s)^n} \quad (20)$$

where n is selected to ensure physical realizability, and τ_f is used to adjust the response speed.

For $\tau_f=1$ and $n=2$, internal model controller based on Frank's method is expressed as follows:

$$C_{Frank}(s) = \frac{s^2+1.1s+0.2}{0.15} \cdot \frac{1}{(1+s)^2} \quad (21)$$

This approach provides a robust controller that reduces noise; however, Frank's method depends on tuning the filter $G_f(s)$ (τ_f, n), which may degrade performance and robustness.

The three controllers PID, Frank-IMC, and GA-IMC-OV were tested on the considered electric furnace. Figure 10 compares their performances in response to a unit step input. The results show that the GA-IMC-OV method achieves the best overall performance: it reaches the setpoint without overshoot, ensuring optimal stability and robustness. It also provides a short settling time of approximately 15 s, while maintaining a smooth and non-oscillatory response.

In comparison, the Frank-IMC controller is slightly faster (0.85 compared to 0.80 for the PID at 10 s) but exhibits about 5% overshoot, which is completely avoided by the GA-IMC-OV approach. PID controller shows the weakest performance, with a slower response (0.80 at 10 s), approximately 8% overshoot, and a longer settling time (25 s). Thus, the GA-IMC-OV method offers the best trade-off between speed, accuracy, and stability, outperforming both Frank-IMC (slightly oscillatory) and PID (slower and less accurate response).

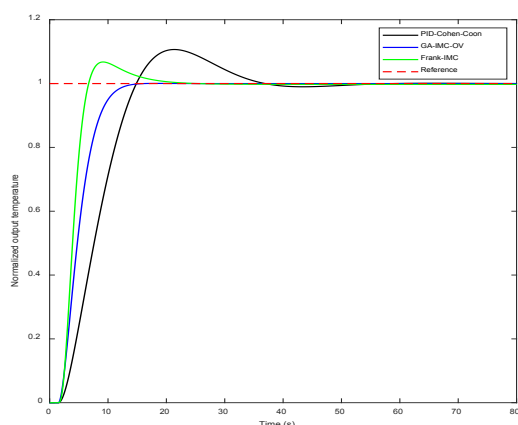


FIGURE 11. Performance Comparison of PID, Frank-IMC, and GA-IMC-OV Controllers

CONCLUSION

In this paper, a novel model inversion technique is proposed for the design of an internal model controller. The proposed structure integrates two established approaches, namely the method introduced by Soudani et al. and Frank's method. The main contribution of this work lies in the use of a genetic algorithm to optimally determine the inversion gain, leading to improved control performance. The use of genetic algorithm is justified by its strong global optimization capability, robustness against local minima, and effectiveness in handling nonlinear multi-parameter tuning problems without gradient information or restrictive assumptions on the cost function. Moreover, the optimization is performed offline, and since the primary objective is to enhance control performance in terms of robustness, stability, and transient response, the computational cost is not a critical constraint in this work.

Two categories of fitness functions were investigated. The first one is based on classical error minimization criteria (ISE, IAE, ITSE, ITAE), while the second focuses on overshoot reduction, where the GA-OV-IMC controller has demonstrated excellent performance by effectively eliminating overshoot and improving system stability. Application to an electric furnace system showed that the second category ensures superior stability and completely eliminates overshoot, although with a slightly slower response time. Future work will focus on combining both objective types to achieve a better trade-off between accuracy, stability, and speed. Finally, comparative results with PID and Frank-IMC controllers demonstrate that the proposed GA-OV-IMC strategy provides the best overall performance, making it the most effective internal model control approach among the tested methods.

In future work, we acknowledge that a truly optimal controller should simultaneously improve all key performance criteria. Therefore, the proposed approach will be extended toward a multi-objective optimization framework, where time, settling time, and overshoot will be jointly optimized using a combined fitness function. This will allow achieving a balanced trade-off between speed, accuracy, and stability, and will further clarify the notion of optimal performance.

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DECLARATION OF COMPETING INTEREST

None.

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