A Bio-inspired Emergent Control Approach for Distributed Processes

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Abstract – The complexity of industrial processes has grown exponentially, with high degrees of dependency, non-linearity, imprecision, among other aspects, which motivates the interest in developing distributed control systems for their management. In this sense, this work proposes a bio-inspired distributed control approach, where control actions emerge from the component interactions. The distributed control approach is based on the response threshold model to solve the control problem by imitating the behavior of ants. Particularly, our approach is inspired by the way as the ants carry out the division of labor in a colony. Thus, our control approach based on the threshold response model refers to the possibility of reacting to stimuli associated with the distributed control tasks. It has the ability to stabilize the process in the presence of abrupt/successive changes and various initial conditions, with a minimum effort of the actuators to achieve the objectives. Also, it has shown its versatility in different operational contexts with the same parameter tuning. The bio-inspired control approach is proved in a quadruple tank process, a complex system due to its multivariate nature. In this way, our paper introduces a new domain of application of the response threshold model in industrial processes. Several experiments were carried out in different contexts to evaluate its stability, robustness, etc., and compare it with other similar works. In general, the control performance metrics show satisfactory results, which reflects its ability to adapt to changes in the dynamics of the process, which encourages additional studies.

Index Terms– Emergent Control, Distributed Control Systems, Response Threshold Model, Quadruple Tank Process**.**

1. INTRODUCTION

Society is permanently demanding new products and services, with high-quality standards, fast response times, personalized solutions, among others [1], which increases the pressure on production systems. For that reason, the industry must adapt continuously its equipment, processes, policies and standards, forcing it to focus on innovative solutions to respond quickly to these demands. This context exhibits typical dynamics of complex systems [2], such as uncertainty, imprecision, nonlinearity, unpredictability, high dependency, a large number of variables, strong constrained, large delay time, among others [3].

Industrial processes require high levels of reliability, availability and safety; therefore, new control strategies must be carried out in controlled environments that allow evaluating and improving theories and strategies emerging. Consequently, several studies have addressed the quadruple tank process as a reference model to illustrate the performances and limitations in the design of control systems [4], which is very complex to control due to the cross interaction in the loops (high degree of dependence). This is a case study where distributed control systems (DCS) can be used due to their nature, understanding that a DCS is a generic term related to versions of multi-task, multi-variable, and multi-loop controllers used in process control [26]. In general, DCS are suitable for processes that can be divided into different functionally independent sections, based on their geographic distribution, and/or management requirements [26], such as the nonlinear MIMO control systems in industrial environments [27] or the quadruple tank process [6] [7] 29]. Therefore, the quadruple tank process is a multivariable system where DCS can be implemented.

Especially, this reference model has been used to test intelligent computing techniques, and to compare them with traditional ('hard') computing techniques that normally rely on deterministic analytic techniques that aim to exactly solve problems while assuming full knowledge of the parameters involved [4]. Intelligent computing, in strict contrast to hard computing, can work with imprecision, uncertainty, and incomplete information, to achieve "good enough" solutions to computationally hard problems at lower costs [5].

However, the distributed proposals based on the MPC (Model predictive control), despite improving the computational cost by reducing the complexity of the subprocesses, incorporates communications problems such as latencies in the network, packet losses, among others, when sharing information between the controllers [6] [7]. Some works that apply bio-inspired strategies involve a learning phase with large volumes of data to find suitable models [13]. Finally, the different works in the literature consider test scenarios without transition between phases.

On the other hand, the term emergent control (EC) is used as an alternative for the control of complex systems, based on a large number of distributed elementary units or agents with control capabilities, so that the desired behavior globally appears due to a distributed control. In general, a multi-agent system (MAS) is a group or community of agents that interact with each other to solve problems that are beyond the capacities or knowledge of each one, allowing the emergence to a higher level [8]. In [9], the authors describe the control that emerges from the interaction of the individuals of a system, as a result of simple control rules. Finally, several works, such as [10] [11], propose to incorporate these concepts in the industrial field.

In this paper is proposed an intelligent technique to achieve emergent control based on the response threshold model, which describes the sensitivity of ants in responding to external or internal stimuli to drive their behavior [12]. Our distributed control approach is inspired by the way the ants carry out the division of labor in a colony. Particularly, the approach refers to the possibility of reacting to stimuli associated with the distributed control tasks. This model has demonstrated its potential to successfully adapt to the various circumstances and dynamics of the environment. Particularly, the contributions of this study are:

- An emerging control scheme where the dynamics of the process are unknown, so that the distributed control elements locally perceive the information available to achieve the desired global control objective from their local control decisions.
- A new application domain for the response threshold model (RTM) to solve control problems. Especially, the control signal is a function of probability, which allows continuous control over industrial processes, that is, the RTM represents a new control strategy. Normally, in the majority of previously identified applications of RTM, they only focus on the discrete control of behaviors such as worker/non-worker, exploration/collection, among others.
- A versatile controller to achieve the desired objectives, where the desired value is achieved despite the transitions between the minimum and non-minimum phases; a situation not considered in any previously reviewed work. The vast majority of the approaches only address the study separately and with different parameters tuning for each phase.

This article is organized as follows: Section 2 presents the related works; Section 3 describes the theoretical framework of the proposed emerging technique and the process to be controlled. Section 4 presents our response threshold model, where the adaptation of the equations, dynamics and optimization processes are highlighted. Section 5 describes the experiments carried out, metrics to evaluate the quality, and the comparison with other works. Finally, are presented the conclusions and future works.

2. Related Works

In this section is presented a review of the literature oriented toward the four tanks that apply distributed optimization models, emerging techniques, bio-inspired or collective intelligence approaches, as well as relevant studies using the RTM. Of the twenty-seven (27) works analyzed, only six (6) incorporate some form of emergent control. Figure 1 shows the relationships between bio-inspiring strategies and the approaches to control the process of the quadruple tanks, showing that PSO (Particle Swarm Optimization), GA (Genetic Algorithms), artificial neural networks (ANN), and fuzzy logic are the most widely used optimization techniques by controllers such as MPC and PID (proportional–integral–derivative) controllers, among others.

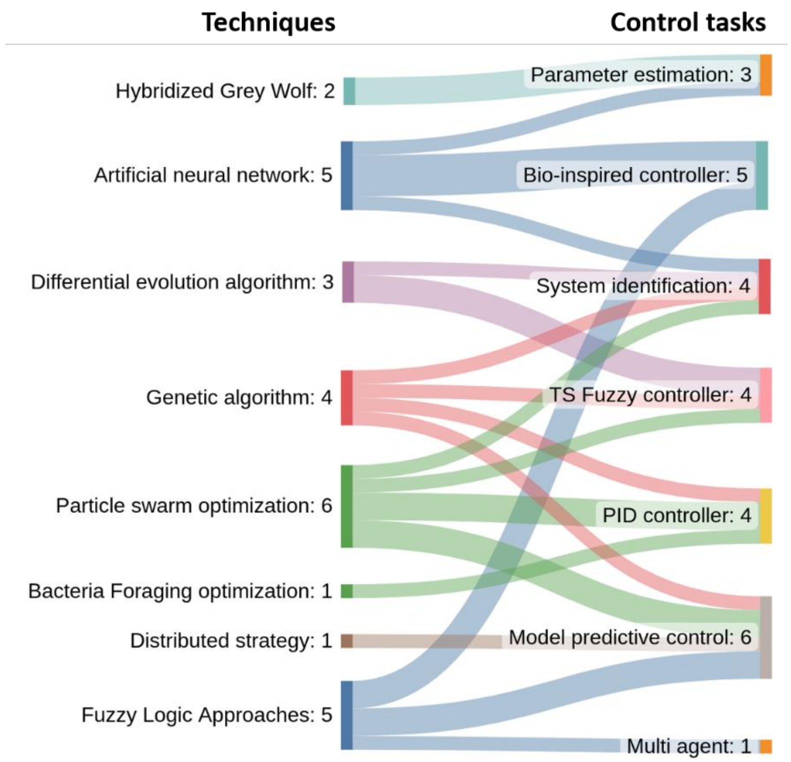


Figure 1. Trends in the application of bio-inspired techniques in QTP

In [6], a decoupling-based cooperative distributed multiparametric model predictive controller (mpMPC) is proposed to solve the benchmark quadruple tank problem; which is compared with other similar control schemes like multiparametric model predictive control (mpMPC), Centralized mp-MPC Control (C-mpMPC), Decentralized mpMPC control (DC-mpMPC), and Cooperative distributed multiparametric MPC, among others. It is concluded that the mpMPC reduces the controller design complexities preserving the performance of a centralized design scheme on the quadruple tank process.

In [7], the authors present a distributed optimal model predictive control (DOMPC) applied to a quadruple tank system, which distributes the control laws to local controllers to achieve the global control objective. They consider the problems of delay in the reception of information and loss of packets. However, this study was applied to slow processes, and the proposed controllers present a great computational burden in solving online optimization problems, which becomes more complex as the number of variables grows. Each local MPC behaves like a centralized MPC controller, but considers the dynamics, constraints, and control objectives of the other subsystems. To do this, each controller solves an optimization problem with local information (decentralized MPC), and exchanges information with the other controllers (distributed MPC), to improve the overall performance of the system. This proposed strategy does not ensure the stability of the closed-loop. Another limitation is that the opening factors of the valves are set before performing the experiments.

Kien et al. [28] propose an adaptive MIMO fuzzy controller optimized with a Jaya optimization technique, applied to control the fluid level of double tank systems. The results confirm that this Adaptive MIMO Fuzzy control method is a robust and simple approach to effectively control highly nonlinear uncertain systems. In [29], a coupled four-tank

MIMO process is controlled for its minimum and non-minimum phase based on a three-block decentralized fuzzy logic control, where each one is specialized in an operating mode defined by the system phase. Simulation results show a useful control response that considers settling time, error band, and overshoot requirements. In [30] proposes an adaptive inverse evolutionary neural (AIEN) controller for liquid level control of the quadruple tank system.

The paper [13] presents a control scheme for nonlinear complex systems and time-variant industrial processes based on reinforced learning algorithms (RL). In this work is proposed an approach that allows learning the optimal control policies, comparing it with strategies such as ANN through a large dataset for training. This proposal is applied to multivariable processes, such as a bio-reactor used for yeast fermentation, and in the four-tank system. Finally, they concluded that the RL control strategy is superior to the ANN control strategies on a wide variety of performance metrics. A fundamental limitation of these control strategies is that extensive training data might be needed to learn such a control model. Also, it is difficult to guarantee the existence and uniqueness of an inverse model of a nonlinear system. Lin et al. [31] propose a neural network that is a self-organizing double function link brain emotional learning controller, which is based on the judgmental and emotional activity of a brain. It has been used in multiple-input multiple-output (MIMO) nonlinear systems.

Teruya et al. [19] propose the use of the RTM to implement an autonomous specialization in swarm robotics. This specialization is conducted using the different sensitivities of different ants to external stimuli, through the utilization of the ratio of workers that an agent touch in a short term as the external stimulus. The proposed model is applied to an ant foraging problem and shows that the model can successfully mimic the assignment of roles in an ant colony by switching between exploring and foraging behaviors.

García et al. [32] carry out a systematic review of the literature on emergent control systems, to deepen their conceptual bases, principles, architectures, and methodologies. Also, they study their role in the context of Cyber-Physical Systems, analyzing their applications and contributions to Industry 4.0, and determining the trends, challenges, and future directions. More recently, the work [33] analyzes the distributed control problem of coordination of the components of a smart grid. They propose a solution to achieve the participation of each component when the conditions are more favorable, such as prioritizing the consumption of renewable energy, or storing the energy surplus, among other things. The distributed strategy of emerging controllers is based on the RTM.

In general, the interest of this study is focused on the emergent control of processes based on bio-inspired techniques, and particularly, for the four-tank process. There are few recent works about this subject, and there are no based on the response threshold model, so it represents a research opportunity.

3. THEORETICAL FRAMEWORK

3.1 The quadruple tank process (QTP)

The quadruple tank process (QTP) was proposed by [14] to illustrate the performance limitations in the design of control systems due to the cross interaction in the loops, which makes it more difficult to control the process variables, that is, this process exhibits characteristics of complex systems where DCS can be implemented. The process consists of four interconnected water tanks with two pumps and two three-way valves, where the inputs are the voltages applied to the pumps and the outputs are the water levels of the two lower tanks. The two upper tanks introduce changes in the dynamics of the process for the adjustment of the valves, by slowing down the response times of the controlled variables. The schematic diagram of the process is illustrated in Figure 2. Later, in Section 4.1, an extension of the process is presented as DCS (see Figure 3).

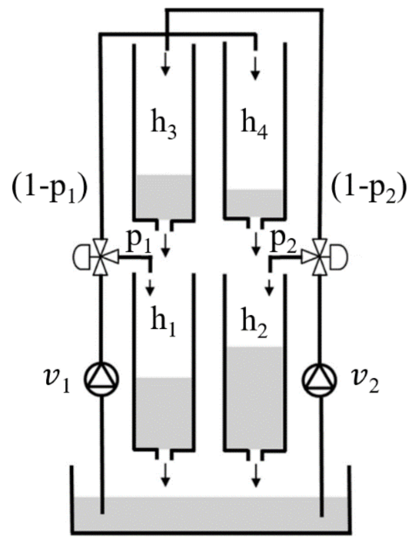


Figure 2. Schematic diagram of the QTP

The process inputs are v_1 and v_2 (input voltages to the pumps), and the outputs are h_1 and h_2 (measured level of tanks). The differential equation model of the QTP, based on the mass balances and Bernoulli's law, is described below:

$$\begin{aligned}
\frac{dh_1}{dt} &= -\frac{a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{p_1 k_1}{A_1} v_1 \\
\frac{dh_2}{dt} &= -\frac{a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{p_2 k_2}{A_2} v_2 \\
\frac{dh_3}{dt} &= -\frac{a_3}{A_3}\sqrt{2gh_3} + \frac{(1-p_2)k_2}{A_3} v_2 \\
\frac{dh_4}{dt} &= -\frac{a_4}{A_4}\sqrt{2gh_4} + \frac{(1-p_1)k_1}{A_4} v_1
\end{aligned} \tag{1}$$

Where, A_j is the cross-section of tank j [cm^2], h_j is the water level of tank j [cm], $p_i \in (0,1)$ is the fraction of flow of water from pump flowing to tank j, a_j is the cross-section of the outlet hole j [cm^2], g is the acceleration of gravity [cm/s^2], k_i is the pumps gain [cm^3/Vs]. In addition, the voltage applied to pump i is v_i, and the corresponding flow is $k_i.v_i$.

The parameters p_i are determined from how the valves are set prior to an experiment. The flow to tank 1 is $p_1.k_1.v_1$ and the flow to tank 4 is $(1-p_1).k_1.v_1$, and similarly for tank 2 and tank 3. The physical meaning is summarized as follows, in minimal phase $(1-p_2) < p_1$, it is easier to control h_1 with v_1 and h_2 with v_2 because the flow is higher towards the lower tanks. Instead, in non-minimal phase $(1-p_2) > p_1$, the flow to the lower tanks is smaller than the flow to the upper tanks. Thus, the control problem is particularly hard because the control is inverse, h_1 with v_2 and h_2 with v_1, slowing down the response times of the controlled variable.

In the current model considered for simulation, the values of these parameters are taken from [14], except the flow ratio and the values that are defined in Table I. Also, the model given by Eq. (1) is solved in Matlab using the ODE 45 solver.

Table I. Model parameters of quadruple tank process

Parameter	Symbol	Value	Units
Tank area	A_{1-3}, A_{2-4}	28 32	cm^2
Restriction area	a_{1-3} a_{2-4}	0.071 0.057	cm^2
Pumps gain	k_1, k_2	3.14, 3.29	cm^3/Vs
Gravitational constant	g	981	cm/s^2

3.2 *Response Threshold Model (RTM)*

Nature has been an invaluable source of inspiration to solve many complex problems [15], like the insect societies that exhibit a variety of behaviors in different contexts, which attract the attention of the scientific community, to understand, model and deploy their dynamics in specific application domains. For example, the general Ant Colony Optimization (ACO) model has been used to solve combinatorial optimization problems [16], where through a distributed algorithm a set of agents, called ants, cooperate themselves to find good solutions. The ACO model follows the behavior of real ants using an indirect form of communication mediated by a pheromone. Otherwise, the RTM [17] mimics the sensitivity of ants to the pheromone intensity or external/internal stimuli, which is based on the behavior of the division of labor in ant colonies, allowing the adaptation of the colony to changing circumstances [18]. For example, ants can have different behaviors depending on their distance to the nest and the ability of each to perform a given task. Thus, the closest ants can care for larvae, eggs and the queen, the ants in the vicinity perform repair work, as well as distribution of food, while ants located further away are responsible for collecting food [19].

In general, the sensitivity to external/internal stimuli can be modeled using a parameter called response threshold θ. An agent with a low response threshold becomes a worker with a high probability, even if external stimuli are weak; whereas an agent with a high response threshold does not become a worker, even if external stimuli are strong [18]. In a conventional response threshold model for the division of labor, an agent has the probability q of work in a given moment according to the following equation:

$$q_j = \frac{s_j(t)^2}{s_j(t)^2 + \theta_{ij}(t)^2} \tag{2}$$

Where θ_{ij} is the response threshold that represents the sensitivity of the ant i to perform task j at time t, and s_j is the external/internal stimulus. This model is used for the task assignment problem, which assumes that each worker responds to a stimulus for a given task, when the intensity of the stimulus exceeds the worker's threshold for that stimulus. In addition, the ants modify the intensity of the accumulated stimulus (s_j) according to equation (3), as a way of exerting control over the system, through an individual or collective learning process, by linking rewards to stimuli [15].

$$s_j(t+1) = s_j(t) + \delta - \frac{\alpha N_{act}}{N} \qquad (3)$$

In the conventional model, the variations in the intensity of the stimulus are due to the execution of the task; where N_{act} is the number of active individuals, N is the number of potential individuals that may be active in the colony, α is a scale factor that measures the efficiency in performing the task, δ is the increase in the intensity of the stimulus per unit of time [18].

On the other hand, when the response threshold is fixed from a simple reinforcement process, the threshold decreases when the corresponding task is performed, and increases when the corresponding task is not performed [20]. This combined reinforcement process gives rise to the appearance of specialized workers, that is, workers are more sensitive to the stimuli with a particular task j, starting from a group of initially identical individuals. The response threshold incorporating reinforcement learning can be expressed as follows:

$$\theta_{ij} = \theta_{ij} - p_{ij}\beta\Delta t + (1 - p_{ij})\gamma\Delta t \qquad (4)$$

Where, β is the learning rate, γ is the forgetting rate, p_{ij} is the fraction of individuals of type i doing task j. Thus, equation (4) indicates that in the next Δt time units, p_{ij} fraction of individuals of type i do task j, and (1 - p_{ij}) fraction do something else or nothing [21] [22]. In this way, the response threshold model refers to the possibility of reacting to stimuli associated with tasks to respond to the problem of division of labor in a colony. In the present study, the RTM is used as a new bioinspired control strategy where the gain is only a scaling factor to achieve an effect on the final control element (pump).

4. DESIGN OF THE CONTROL WITH RTM

4.1 Mathematical model

In this section, the RTM applied to the process control of quadruple tanks is formally presented; where the pumps as final control elements are part of the ants o agents in the model, and the stimuli (s) are given by the local variables available in the environment, such as the levels of the tanks to be controlled. The sensitivity of the response threshold θ_{ij} is a variable that helps to determine the tendency of an individual i to respond to stimuli and perform the task j associated with s_j. In addition, the principles of emergent systems are adopted, such that each controller i (EC_i)

perceives only the local variables h_j and the desired value level h_{jsp} of its sub-process, as shown in Figure 3. Also, there are interactions between them, in order to share local information Δh_j with other remote controllers to achieve global goals together. Figure 3 shows a definition of the QTP as DCS. Subprocess 1 is made up of tanks 1 and 4 that are filled by pump 1, and subprocess 2 is made up of tanks 2 and 3, affected by pump 2. In addition, tanks 3 and 4 influence the controlled variables h_1 and h_2. On the other hand, subprocesses 1 and 2 may be far away, which implies that the local signals/variables that must be shared between them must be sent through the communication channels (in the case of QTP, Δh_1, Δh_2, p_1 and p_2). This may cause additional problems inherent to DCS, such as the cost of communication due to signal transmission delays, among other things. However, they are not considered in this study, and will be discussed in future works.

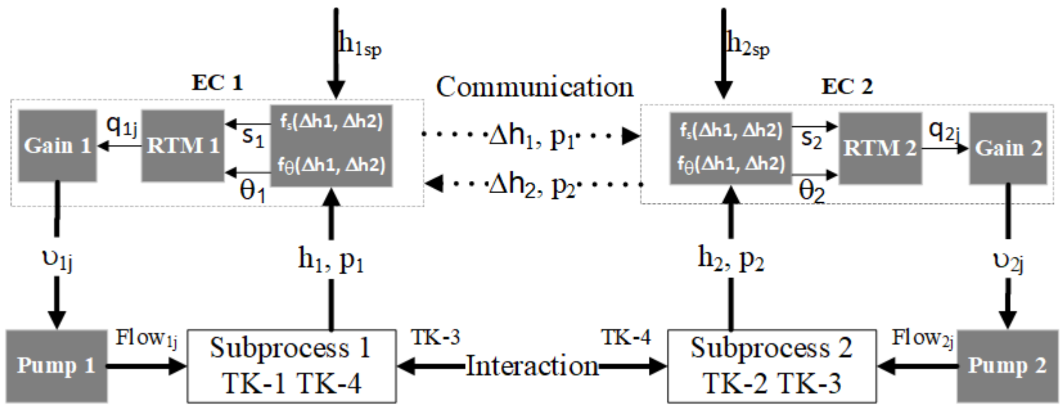


Figure 3. Response Threshold-based emergent control (tr-EC)

The equations presented in the previous section are used together to model and display work division behaviors in a colony of ants. Making use of equation (2), the probability of reaction of the agents (activation/deactivation) is determined, influenced by the external/internal stimuli s_j and the degree of sensitivity θ_{ij}. Particularly, p_{ij} is the fraction of the flow of water from pump i (ant) flowing to tank j (task), h_{jsp} is the reference level, v_{ij} is the voltage as a control signal for the pump, $Flow_{ij}$ is the manipulated variable and w is the attenuation factor

The pump voltage v_{ij} is directly proportional to q_j, according to equation (5).

$$v_{ij} \leftarrow q_j = \frac{s_j(t)^2}{s_j(t)^2 + \theta_{ij}(t)^2} \tag{5}$$

The sensitivity of the response threshold θ_{ij} is a function of the accumulated experiences over time, as well as the local variables (tank level) and the coefficients of the valves p_i, according to equation (4). Those that contribute to the objectives (workers) are defined by equation (6) and are affected by the learning factor β in equation (8), decreasing the response threshold θ_{ij}, and those that do not affect the objectives (non-workers) are defined by equation (7) and are regulated by the forgetting factor γ in equation (8), increasing the threshold. The symbol * represents the ant or controller neighboring.

$$p_i \Delta h_j + (1 - p_{i*}) \Delta h_{j*} \tag{6}$$

$$p_{i*} \Delta h_{j*} + (1 - p_i) \Delta h_j \tag{7}$$

$$\theta_{ij} = \theta_{ij} - \beta \left(p_i \Delta h_j + (1 - p_{i*}) \Delta h_{j*} \right) + \gamma \left(p_{i*} \Delta h_{j*} + (1 - p_i) \Delta h_j \right) \tag{8}$$

To formulate the stimulus, a different proposal is used to that presented in equation (3), which is aimed at obtaining local information from the environment, such as the deviation of the level h_j of each tank in relation to the reference h_{jsp} represented as the system demand, grouped according to their contribution to the control objectives without considering the sign. Thus, workers are represented in equation (9) and no workers in equation (10), which is attenuated by the factor w to make the variations of the perceived signals less sensitive (11):

$$p_i |\Delta h_j| + (1 - p_{i*}) |\Delta h_{j*}| \tag{9}$$

$$p_{i*} |\Delta h_{j*}| + (1 - p_i) |\Delta h_j| \tag{10}$$

$$\begin{aligned} s_j = s_j + w\big[& p_i |\Delta h_j| + (1 - p_{i*}) |\Delta h_{j*}| - (p_{i*} |\Delta h_{j*}| \\ & + (1 - p_i) |\Delta h_j|) \big] \end{aligned} \tag{11}$$

Where,

$$\Delta h_j = h_{jsp} - h_j \in \mathcal{R} \tag{12}$$

Finally, an emergent controller inspired by the behavior of ant colonies is achieved, where the response threshold allows control actions to be exercised over tasks j (level of the lower tanks) represented by the stimulus function s_j. Furthermore, each pump will independently perceive the stimuli, adjusting its influence when the desired level has not been reached in the tanks, expressed through the following equation:

$$v_{ij} = Gain_i \, q_j = Gain_i \frac{s_j(t)^2}{s_j(t)^2 + \theta_{ij}(t)^2} \tag{13}$$

The calculation of the controller gain is carried out assuming the initial conditions of the process, where we suppose that the probability function q is in the middle of the range (0.5). The initial output voltage v_{ij} is obtained experimentally to achieve equilibrium when the deviation Δh_j in the lower tank levels is zero. For this, the control loop is closed, identifying the final control voltage or signal ${v_{ij}}^0$ where equilibrium is achieved to be configured at the start of the experiment, avoiding slight oscillations in control actions that affect quality metrics.

$$Gain_i = \frac{{v_{ij}}^0}{q_j} = \frac{{v_{ij}}^0}{0.5} = 2\, {v_{ij}}^0 \tag{14}$$

The equations for each emergent controller would be as follows:

For agent or ant 1:

$$\begin{aligned} s_1 &= s_1 + w[p_1|\Delta h_1| + (1-p_2)|\Delta h_2| - (p_2|\Delta h_2| \\ &\quad + (1-p_1)|\Delta h_1|)] \\ \theta_{1j} &= \theta_{1j} - \beta\,(p_1\Delta h_1 + (1-p_2)\Delta h_2) + \gamma(p_2\Delta h_2 \\ &\quad + (1-p_1)\Delta h_1) \\ v_{1j} &= Gain_1 \frac{{s_1}^2}{{s_1}^2 + {\theta_{1j}}^2} \end{aligned} \tag{15}$$

For agent or ant 2:

$$\begin{aligned} s_2 &= s_2 + w[p_2|\Delta h_2| + (1-p_1)|\Delta h_1| - (p_1|\Delta h_1| \\ &\quad + (1-p_2)|\Delta h_2|)] \\ \theta_{2j} &= \theta_{2j} - \beta\,(p_2\Delta h_2 + (1-p_1)\Delta h_1) + \gamma(p_1\Delta h_1 \\ &\quad + (1-p_2)\Delta h_2) \\ v_{2j} &= Gain_2 \frac{{s_2}^2}{{s_2}^2 + {\theta_{2j}}^2} \end{aligned} \tag{16}$$

Particularly, equations (15) and (16) present the mechanism used to solve the control problem based on the response threshold model. Our approach mimics the behavior of ants to respond based on stimuli perceived both locally as from the information shared by other neighboring ants (See Figure 3). On the other hand, the satisfaction of the demand in both sub-processes is when $\Delta h_1 = 0$ and $\Delta h_2 = 0$, a situation that causes the stabilization of equations (6), (7), (9) and (10). Our approach determines the reaction of each ant to meet the demands of the process. When the probability function is high it means that the ant must react quickly, and when it is low it responds slowly. In the next section, the macro algorithm that makes this control scheme possible is explained in detail

4.2 Macro algorithm

In this section, the behavior of the proposed emerging controller is explained through a macro algorithm (see Table II).

Table II. Control scheme inspired on RTM (Macro algorithm 1)

Input: Initial conditions (${v_{ij}}^0,\ s_j^0,\ \theta_{ij}^0$, w, Gain$_{i,}$ β, γ) and setpoints h_{jsp} (12) are defined

Procedure:

1. Read the local variable h_j (tank level) and valve coefficient p_i of the associated subprocess
2. Request variables from the neighbors like Δh_{j*} y p_{i*}
3. While Δh_j *or* Δh_{j*} be different from zero (0)
    - 3.1. Estimate the effect of workers (9) and non-workers (10) to calculate the stimulus s_j
        - 3.1.1. If workers is greater than non-workers
            - 3.1.1.1. The stimulus decreases by an attenuation factor w
        - 3.1.2. Otherwise
            - 3.1.2.1. The stimulus increases by an attenuation factor w
    - 3.2. Estimate the effect of workers (6) and non-workers (7) to calculate the sensitivity θ_{ij}
        - 3.2.1. If workers are higher than non-workers
            - 3.2.1.1. Response threshold decreases
        - 3.2.2. Otherwise
            - 3.2.2.1. Response threshold increases
    - 3.3. Calculate the control signal v_{ij} **Error! Reference source not found.**
        - 3.3.1. Calculate the probability of the RTM model (5) to express the degree of reaction or speed of response of the emergent controller
        - 3.3.2. Multiply the probability by the gain to cover the operating range of the final control element (pump)

Output: Control signal v_{ij}

The process starts when the initial conditions are defined, such as the control signal, the stimulus and the response threshold. On the other hand, the attenuation factor is used to reduce the sensitivity of the stimulus, the gain of the controller covers the operating range of the final control element, and the learning/forgetting factors are obtained through a hyperparameter optimization process.

In the distributed control scheme, each ant perceives the local variables, such as tank level and coefficient of the valve associated with the sub-process (step 1). Then, it requests the neighboring ants for the same variables to establish in both cases the difference or error with respect to the setpoints (step 2). Next, a loop starts while the difference between the errors of the controlled variables persists (step 3). In the interactions, the stimulus value (step 3.1) and the response threshold (step 3.2) are adjusted, in order to stabilize the probability according to an adequate relationship between the stimulus and the response threshold to achieve the control objectives. Thus, the stimulus and response threshold values converge at some point during the iteration process when errors become zero.

5. EXPERIMENTS

5.1 Experimental protocol

To validate the proposed controller in Section 4, we address some case studies, each with different interesting properties. The results of these experiments are analyzed and compared with other controllers. The experiments were conducted on a MATLAB R2017b platform. The experiments recreate the different operational scenarios that the controllers may face, such as following a desired reference (in this work, called "reference tracing"), external disturbances, variations in the parameters of the system components (gain of the pumps k_c), changes in the dynamics of the process (transition between the minimum and non-minimal phases) and rising/falling process.

The quality of the results obtained will be evaluated using the next performance criteria [23]:

- Integral square error (ISE) penalizes errors with large values in opposition to smaller errors. Large values of the control error usually occur immediately after a disturbance and can be observed as the overshoot. Thus, this index is mostly used to indicate overshoot and aggressive control.

$$ISE = \int_{t_1}^{t_2} \varepsilon(t)^2 dt \qquad (17)$$

- Integral Absolute Error (IAE) does not distinguish between positive and negative contributions to the error. It is often used for online controller tuning. This index is appropriate for non-monotonic step responses and all kinds of normal operation data.

$$IAE = \int_{t^1}^{t^2} |\varepsilon(t)| dt \qquad (18)$$

- Integral of the Time Weighted Absolute Error (ITAE) is a very conservative performance index. It strongly weights larger errors that occur late in time, while less emphasis is placed on the initial control errors. A large value reflects a bigger loop deviation. The ITAE index trades-off between the error magnitude and its settling time.

$$ITAE = \int_{t_1}^{t^2} t|\varepsilon(t)| dt \qquad (19)$$

An appropriate choice of objective function J is a vital step in solving hyperparameter optimization of our model, which was defined by the equation (15), in order to achieve a faster settling time (see [23] where there is a discussion about this), where ITAE1 and ITAE2 correspond to the quality metric of ant 1 and ant 2, respectively. Particularly, it was used the search grid algorithm to adjust the parameters of our model.

$$Ji = min(ITAE_1 + ITAE_2) \tag{20}$$

The selection criteria of the works that will be used to compare our proposal are those that use in some way emerging principles or collective intelligence techniques as controllers, such as [6] that proposes a control scheme for nonlinear complex systems.

5.2 Tests and Discussions

In this section are present some case studies in order to show the versatility of our approach. The emerging controller based on the RTM proposed imitates the ability of ants to self-regulate their behavior (response threshold) based on external stimuli, generated in the local environment, through stigmergic communication processes (tank levels), to produce complex patterns of behavior (controlled variables).

Case study 1: Calibration tests in minimum and no-minimum phases.

The main objective of the test is to obtain the optimal values of the proposed controller for each mode of operation of the process, as explained in section 3.1 because they represent different dynamics as a consequence of the relationship between the controlled variables (h_1 and h_2) and the water flow of the pumps (v_1 and v_2). Thus, in the minimum phase, the level of tank 1 (h_1) is controlled by v_1, but in the non-minimum phase the control relationship is crossed with v_2, incorporating the slowdown in the control process due to the significant effect of the upper tanks (h_3 and h_4); also presenting the same situation the tank 2.

It should be noted that optimal values will be obtained for both phases, which will allow for quick and smooth convergence to the desired value in the control actions; taking as reference the initial conditions presented in Table III. The levels of the lower tanks (h_1, h_2), valve coefficients (p_1 / p_2) and setpoints, were adopted from [6] to guarantee comparisons with similar works.

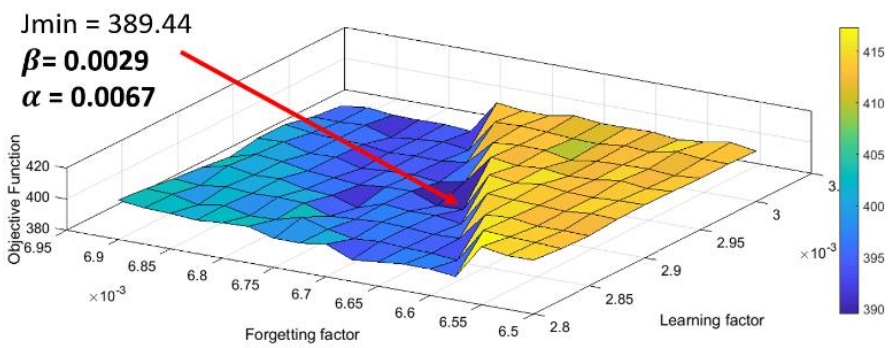
On the other hand, the controller gains ($Gain_1$/ $Gain_2$) were obtained through equation 14, and finally, the voltage of the pumps (v_{1j}^0 / v_{2j}^0), the level of the upper tanks (h_3 and h_4), the stimulus (s_1^0 / s_2^0), response threshold (θ_{1j}/ θ_{2j}) and attenuation factor w were obtained experimentally, keeping the setpoints constant in time to find the controller breakeven point.

Table III. Initial process conditions in the case study

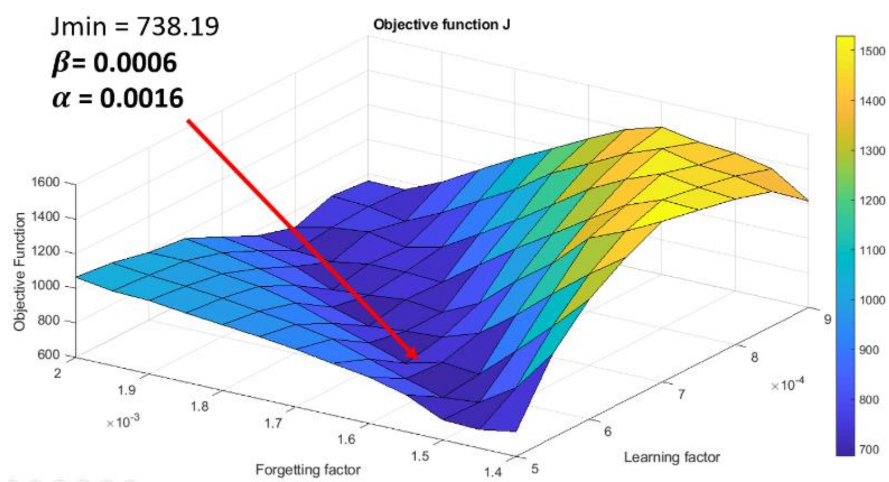
Parameter	Symbol	No-minimum	Minimum
Valve coefficients	p_1 / p_2	0.35 / 0.35	0.7 / 0.6
Initial level [cm]	h_1^0 / h_2^0	10.43 / 15.98	
	h_3^0 / h_4^0	4.472 / 6.652	2.902 / 0.664
Setpoints [cm]	$h_{1\text{sp}}/h_{2\text{sp}}$	16.70 / 18.10	
Pump’s initial output voltage [V]	v_{1j}^0 / v_{2j}^0	3.1906/3.1098	2.184 / 4.071
Controller gain	$Gain_1$/ $Gain_2$	6.38 / 6.22	4.366 / 8.142
Initial stimulus s_i	s_1^0 / s_2^0	100 / 100	

Parameter	Symbol	No-minimum	Minimum
Initial response threshold θ_{ij}	$\theta_{1j}/\ \theta_{2j}$	100 / 100	
Attenuation factor	W	0.0029	

For the hyperparameter optimization process, according to equation (20), the exploitation area was carried out around the value that minimized the objective function. It can be seen that the surface in the minimum phase (see Figure 4.a) presents a greater uniformity, the best performance of the controller, and higher values in the hyperparameters. On the other hand, in the non-minimum phase (see Figure 4.b), the surface is more abrupt, which affects its performance, in addition to smaller values of the hyperparameters.



(a)



(b)

Figure 4**.** Optimization of hyperparameters in (a) minimum and (b) no-minimum phases

Figure 5 shows the behavior of the process in each phase, establishing initial conditions to achieve the equilibrium of the process, in a context with simultaneous changes in the setpoints. The coefficients of the valves $p_1/\ p_2$ are defined at the beginning of the experiment to determine the operating zone of the controller (minimum / non-minimum phases).

On the right side of Figure 5, in both cases, there is convergence around the desired value, with an oscillatory behavior. The differences lie in the settling time, since in the minimum phase (see Figure 5.a) will be achieved faster than in the non-minimum phase (see Figure 5.b) due to the nature of the processes, as stated in section 3.1. It can also be seen that overshoots on h_1 and h_2 in both phases are slight. Additionally, the output voltage of the pumps exhibit dynamics within the normal operating range of the process, without abrupt changes, evidenced in the central Figures 5.a and 5.b. The left side of Figures 5.a and 5.b shows the stimulus of each agent based on the local variables of the environment to perceive the variations. In particular, the left side of Figures 5.a and 5.b show the simultaneous change of the setpoints and tank levels in the quadruple tank process. The agents use these stimuli to define the control actions, according to the probability function defined previously that varies continuously to govern the pump, achieving an analog control of the process, highlighted as a new application for the RTM.

Using the quality metrics from the previous section, several objective functions to be optimized were defined, in order to carry out a sensitivity analysis of the process variables (h_1 and h_2), the parameters of the RTM model (β and γ), the quality of the control approach (ISE, ITAE and IAE), and the convergence. Table IV presents this analysis, such that the hyper-parameterization process used guarantees an accelerated convergence process without degrading quality. In particular, the feedback process (reinforcement learning) is studied, which in our case occurs for two variables: response threshold and stimuli. It can be seen in Tables IV.b and IV.c that for the two specific objective functions indicated therein, similar values are achieved in each of the quality metrics, both in the minimum and non-minimum phases. Furthermore, the learning and forgetting factor parameters converge to the same value. On the other hand, the objective function of Table IV.a has a faster convergence, and also, the quality metrics improve considerably. In this sense, it allows achieving better quality and faster response from the controller. Thus, in the rest of the work, said objective function is taken as a reference (equation 20).

Table IV. Performance metrics in case study 1

a) Objective function with $Ji = min(ITAE_1 + ITAE_2)$

Metrics	**No-minimum** $\beta = 0.0006$ $\gamma = 0.0016$		**Minimum** $\beta = 0.0029$ $\gamma = 0.0067$	
	h_1	**h_2**	**h_1**	**h_2**
ISE	79.44	9.25	27.49	6.18
IAE	19.78	10.19	9.96	6.61
ITAE	463.44	274.75	228.50	160.94

b) Objective function with $Ji = min(IAE_1 + IAE_2)$

Metrics	**No-minimum** $\beta = 0.00026$ $\gamma = 0.0066$		**Minimum** $\beta = 0.01$ $\gamma = 0.0027$	
	h1	**h2**	**h1**	**h2**
ISE	1354	455.9	42.86	18.46
IAE	854.4	538.4	96.86	79.55
ITAE	254100	249900	15510	15560

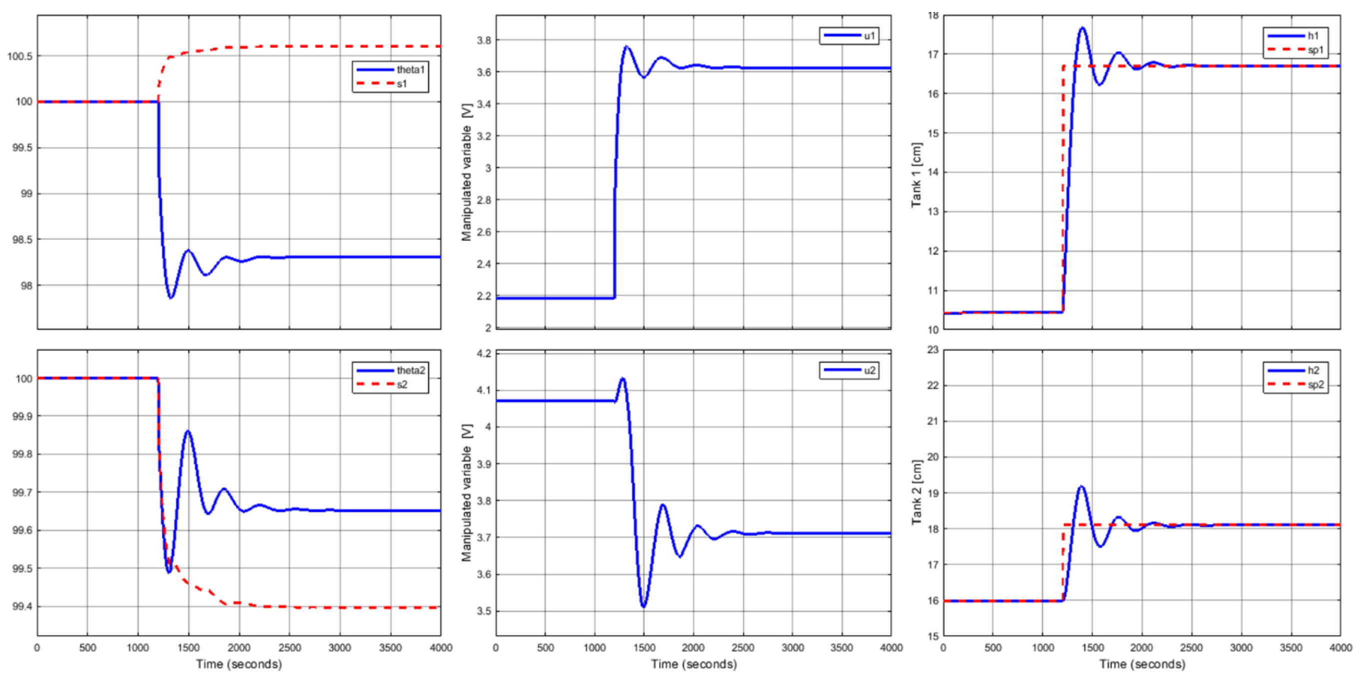
c) Objective function with $Ji = min(ISE_1 + ISE_2)$

Metrics	**No-minimum** $\beta = 0.00026$ $\gamma = 0.0066$		**Minimum** $\beta = 0.01$ $\gamma = 0.0027$	
	h1	**h2**	**h1**	**h2**
ISE	1354	455.9	42.22	18.56
IAE	854.4	538.4	95.71	79.59
ITAE	254100	249900	15520	15540

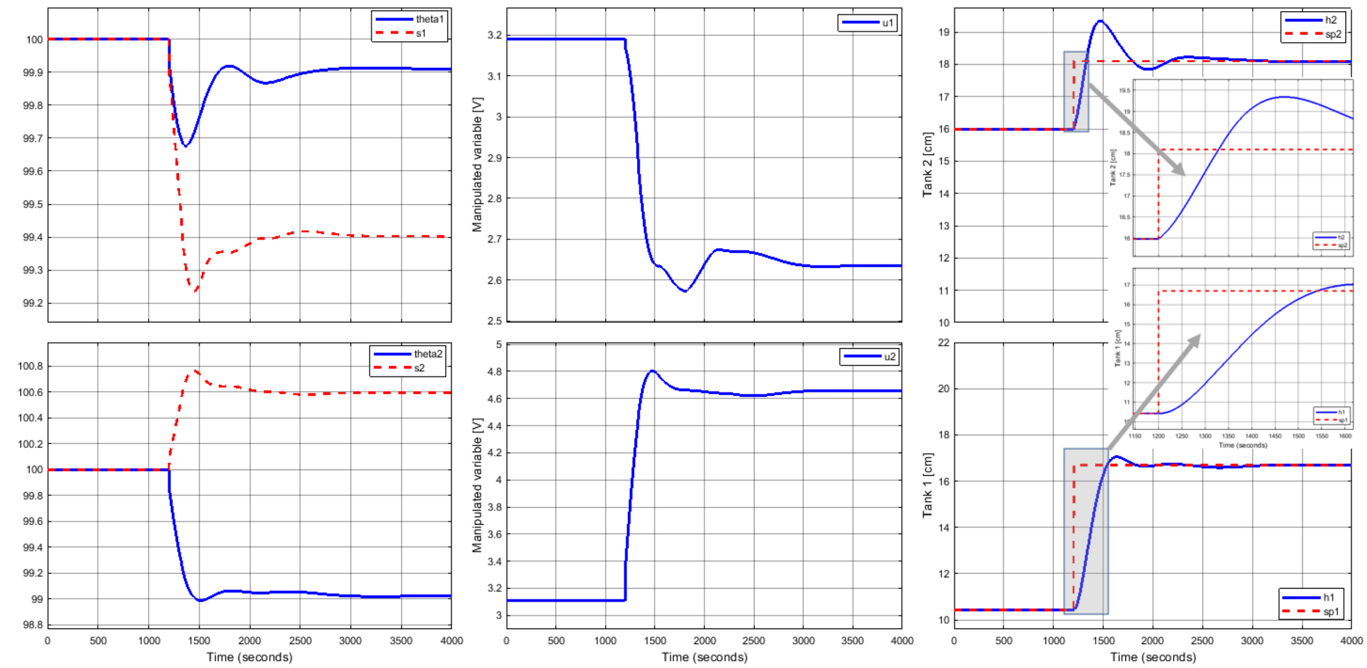
The previous description of the process of Figure 4 can be quantified through the performance metrics presented in Table IV.a, where it is observed that the ISE, IAE and ITAE are lower in the minimum than in the non-minimum phase, due to the fast response times that characterize this mode of operation. However, it should be noted that in both phases the metrics were better in tank 2 than in tank 1 because the change in the setpoints is less.

It should be noted that the high metrics in the non-minimum phase of 79.44 in ISE and 463.44 in ITAE in tank 1 level are due to the changes in the setpoints is greater in tank 1, which causes a delay to reach the new reference (2.56 times higher in tank 1, see Figure 5.b). That is, in tank 2 it is achieved in 132 seconds while in tank 1 in approximately 340 seconds, reflected in a greater deviation in the error for a longer period of time.

Finally, it is concluded that the emergent controller proposal based on the RTM (tr-EC) can convert a discrete control probability function into a continuous one based on the basic concepts of stimulus and threshold, to adjust the voltage of the pumps for controlling the lower tanks, both in minimal and non-minimal phase; showing that the learning and forgetting factors are different for both cases due to the difference that governs the dynamics of the system, but the established control objectives will be achieved. Another important aspect to highlight is that the deviation in the setpoints at the time of the transition affects the quality metrics, due to the effort made by the pumps to stabilize the process, which translates into oscillations and times. A detailed stability study is presented in section 5.3 to analyze convergence when different initial conditions are established.



(a)



(b)

Figure 5. Process response in case study 1 in a) minimal and b) no-minimal phases

Case study 2: Reference tracing

The objective of this test is to evaluate the follow-up of the controlled variables (h_1 and h_2) to the successive and/or simultaneous change of the setpoints during the simulation, to analyze the response of the proposed emergent controller to positive and/or negative transitions in no-minimum phase; being a dynamic widely studied due to the dependence between the control loops and their slowing down processes. For this case, the same parameters presented in Table I will be taken.

In Figures 6.c and 6.f, a common behavior is observed in both tanks, such as convergence around the new set points. However, each controlled variable does it differently: when the setpoints grow then the stabilization time is faster. On the other hand, when the setpoints is reduced then it is slower with pronounced negative peaks in tank 2, as shown in Figure 6.c. In tank 1 it is gradual (see Figure 6.f) due to the response of each of the controllers to the voltage applied to the pumps, as shown in Figures 6.b and 6.e, caused by the relationship between the stimulus and the threshold, where there is a greater increase in the setpoints in tank 1 that causes s_2 to increase in Figure 6.d. However, s_1 decreases in Figure 6.a to compensate for the sudden increase in the tank that exerts a greater influence on the process.

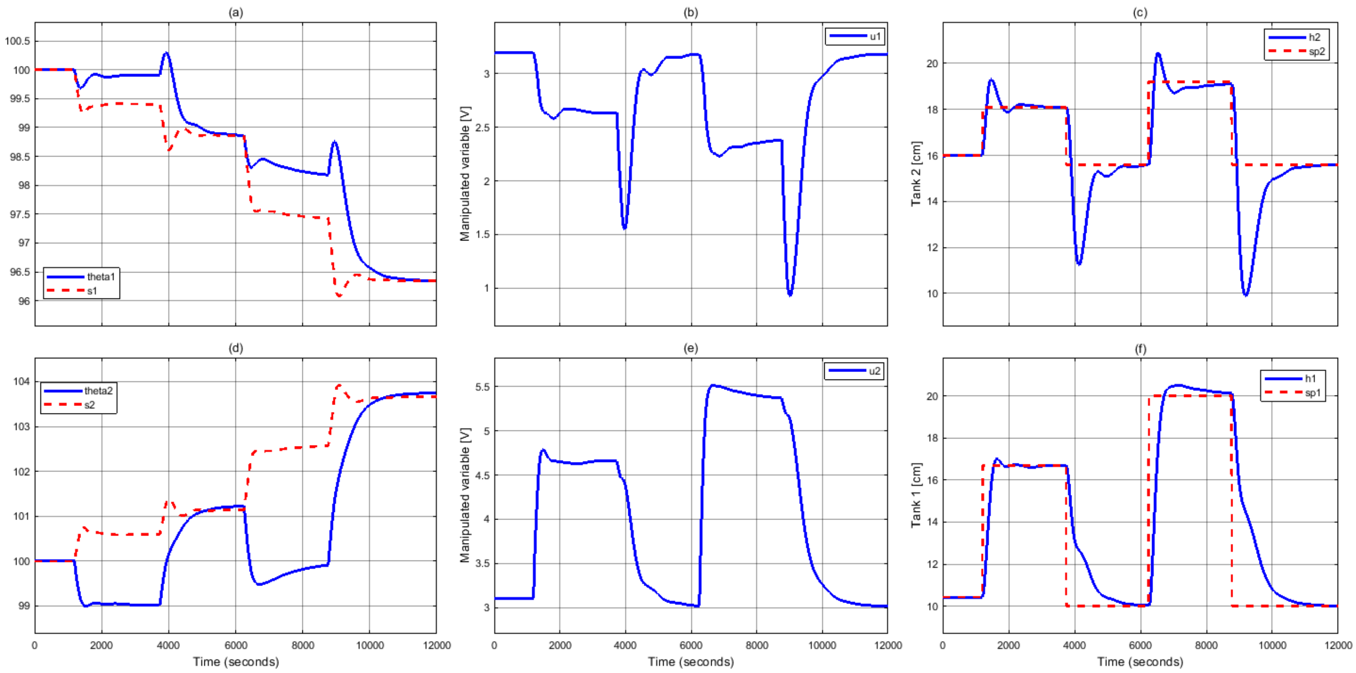


Figure 6. Process response in case study 2 - Reference tracing (SERVO)

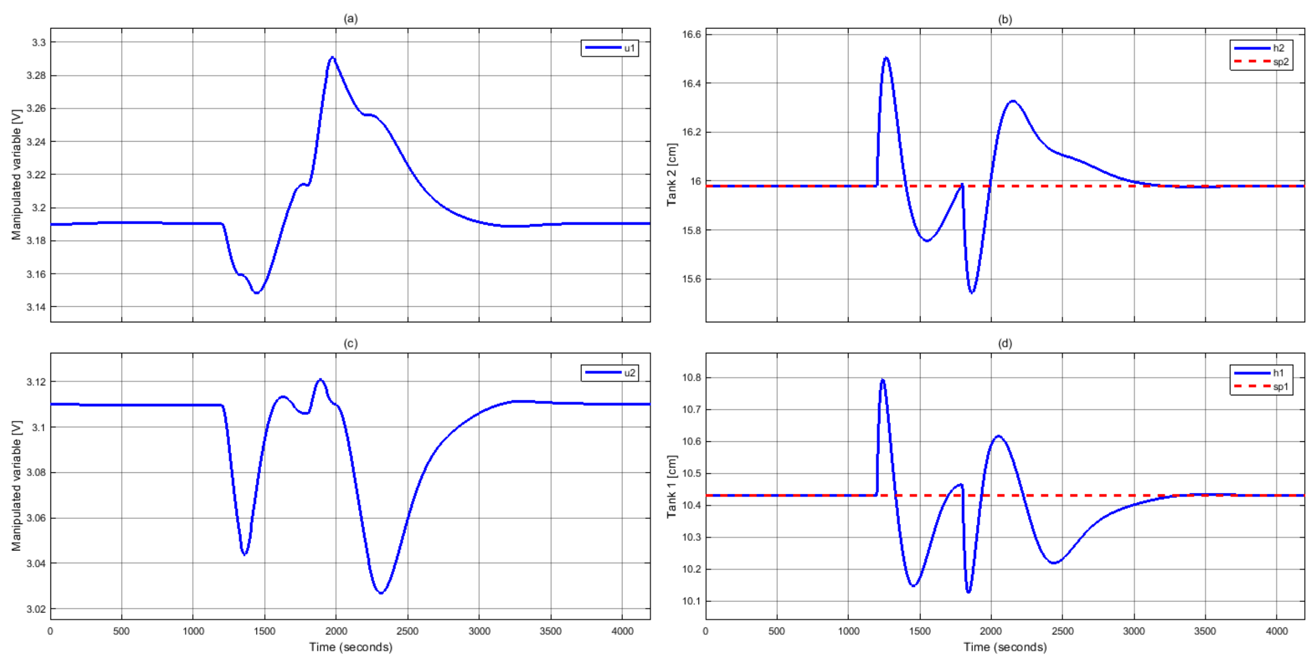


Figure 7. Process response in case study 3 - External disturbance rejection (DIS)

The performance metrics are presented in Table V, which show that the errors over time are lower in tank 2 than in tank 1, despite the peaks that are presented, they normalize quickly. In general, the controlled variable h_2 stabilizes in a shorter time, evidenced in its value of 15706 for ITAE and 2.44 times lower (389,20) in ISE than tank 1 (951,09), motivated by the lower step of the setpoints when adjustments are made over time.

Table V. Performance metrics for reference tracing

Metrics	h1	h2
ISE	951,09	389,20
IAE	203,11	135,36
ITAE	22490	15706

In general, with this test, it was shown that in the event of successive setpoints changes and ascending/descending transitions, the desired control actions are satisfactorily achieved, with fast response times with the increase of the desired value and slow with the opposite behavior.

Case study 3: External disturbance rejection

The objective of this case is to analyze the robustness of the controller, in the face of unforeseen external disturbances that may take the process out of equilibrium conditions, creating an additional flow in tanks 3 and 4, sequentially, which constituted 10% of nominal flow rates to respective tanks for a period of 10 min.

The results obtained in both tanks (see Figures 7.b and 7.d) demonstrate the great robustness of the emergent controller, evident in the little effort made by the pumps (see Figures 7.a and 7.c) to maintain the desired levels and react to any external disturbances.

Table VI shows the metrics taken from [6], which will be used to compare the cases of reference tracing (SERVO) and external disturbance rejection (DIST), with the proposed controller (tr-EC), in the same scenarios, initial conditions and quality metrics (IAE, ISE). To start with the SERVO mode, all the analyzed controllers show that the control of tank 2 is less than tank 1, but the emergent controller has quantitatively better metrics four (4) times less than CD-mpMPC. The other works show high ISE values because it penalizes errors with large values as opposed to minor errors, unlike the one proposed in this article, due to its rapid convergence and reduced magnitude in the peaks.

Table VI. Performance comparison of controllers for servo tracing and disturbance rejection

Measure	Controller type											
	DC-PI[a]		C-mpMPC[b]		DC-mpMPC[c]		CG-MPC[d]		CD-mpMPC[e]		tr-EC[f]	
	h_1	h_2	h_1	h_2	h_1	h_2	h_1	h_2	h_1	h_2	h_1	h_2
IAE_{servo}	1082	467	713	467	2114	712	1011	678	897	419	203,11	135,36
ISE_{servo}	6294	6102	3149	3516	13915	9609	6579	6895	3850	5285	951,09	389,20
IAE_{dist}	71.23	195.04	41.52	31.71	93.99	205	91.26	225.3	44.62	54.15	4.08	5.40
ISE_{dist}	34.86	130.48	5.84	3.67	43.84	151.34	60.05	155.3	15.86	18.27	0.75	1.43

[a] DC-PI – Decentralized PI.
[b] C-mpMPC – Centralized mpMPC.
[c] DC-mpMPC – Decentralized mpMPC.
[d] CG-MPC – Cooperative Game Theory MPC.
[e] CD-mpMPC – Cooperative Distributed mp-MPC.
[f] tr-EC Response Threshold-based Emergent Controller (Our proposal)

In DIST mode, the opposite occurs to SERVO, since the performance in the controller of tank 1 is better than tank 2 because it has faster response times to disturbances; in addition, the absence of peaks is demonstrated, since the ISE values are better than IAE, due to errors being small or less than 1 during the stabilization process. Finally, the performance of the proposed controller in relation to IAE of the CD-mpMPC is reduced by approximately 10 times.

Case study 4: Analysis of the robustness of the controller

The objective of this case is to analyze the behavior of the controller, when there are variations in the manufacturing characteristics of the final control elements, such as pumps, where despite being equipment manufactured by the same suppliers and conditions, they present slight variations in some of the internal parameters of its components considered as constant [6]. Table VII shows the pump flow coefficients k_1 and k_2 are varied by ± 20%, which will allow analyzing the ability of the tr-EC to control within the stable limits.

Table VII. Performance metrics for analysis of the robustness

Metrics	**-20%**		**Nominal**		**+20%**	
	k1	**k2**	**k1**	**k2**	**k1**	**k2**
Pumps gain	2.51	2.63	3.14	3.29	3.77	3.95

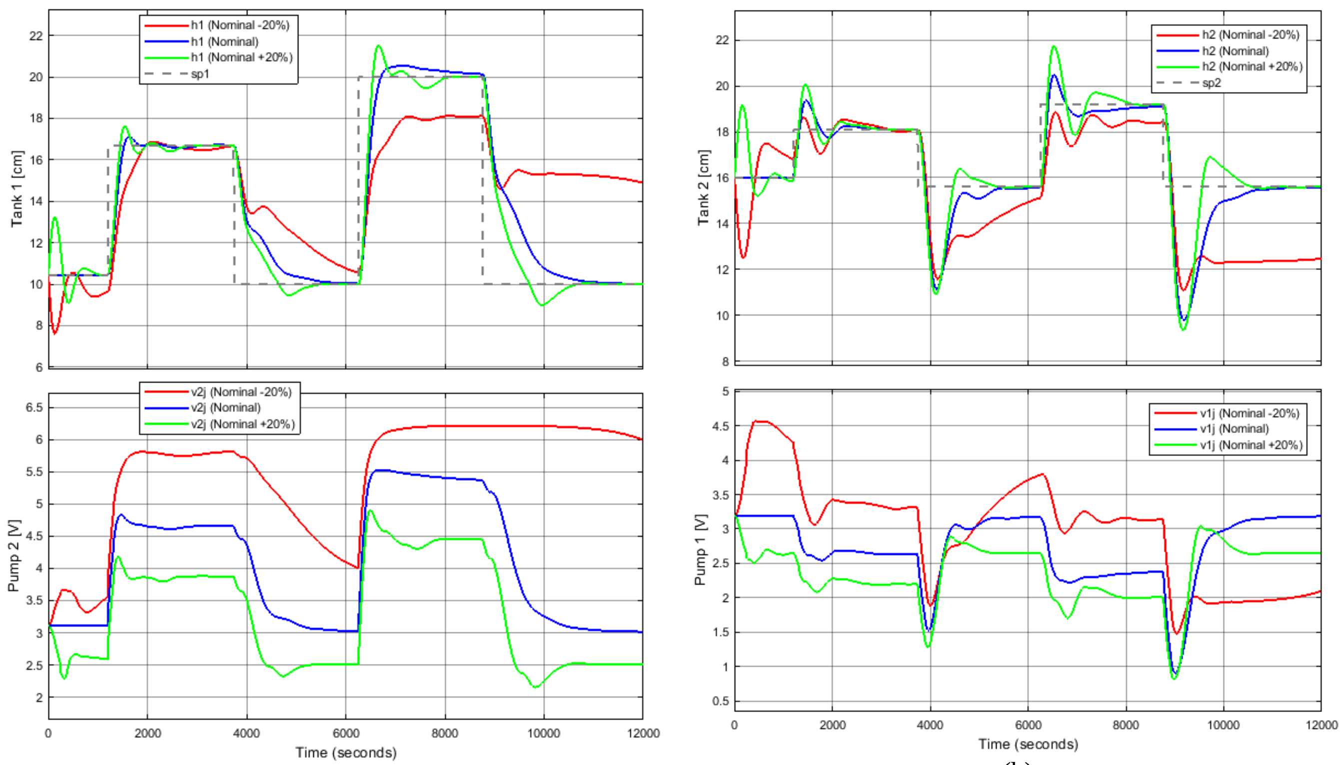
Figure 8.a shows the behavior of the control pair $v_{2j} - h_1$, where the behavior in each case is displayed through the colors. It should be noted that for values of k_1 and k_2 greater than the nominal (green and blue), there is convergence in the setpoints despite the oscillations, unlike values from k to -20% (red) that cannot meet all control demands. A similar situation is presented in Figure 8.b for pair $v_{1j} - h_2$. Also, the level of tank 2 (see Figure 8.b) performs better than tank 1 (see Figure 8.a) because the change in setpoints is less. The lower graphics in Figure 8 show the behavior of the voltage or control signal, where it is observed in both cases that the red lines (-20%) show higher voltage values but are insufficient to exercise control actions due to the valve coefficient k.

In Table VIII is possible to quantify the behavior described above, for the pump coefficients of -20%, the quality metrics, both in error and in time, increase considerably, due to the non-convergence of the control actions (72882 for ITAE). For the valve coefficient of + 20% (14964 for ITAE), it is shown that it reaches the desired value more quickly than the nominal one with an ITAE of 15706, even the error decreases for h1 due to the low oscillations, unlike h_2.

Table VIII. Performance metrics for analysis of the robustness

Metrics	**-20%**		**Nominal**		**+20%**	
	h1	**h2**	**h1**	**h2**	**h1**	**h2**
ISE	2539.30	852.40	951,09	389,20	782.14	424.67
IAE	567.65	328.68	203,11	135,36	174.59	150.46
ITAE	72882	41462	22490	15706	16851	14964

The results show that our approach adjusts automatically the control actions and the nominal flow rates while performing servo tracing with varied model parameters, hence displaying robustness for values of k greater than the nominal, but it is evident that for k less there is a clear loss of control functionalities, which could be self-compensated by the controller to achieve control objectives in future work.



(a) (b)

Figure 8**.** Process response in case study 4 - analysis of the robustness

Case study 5: Transition between the minimum and non-minimum phase

The objective of this test is to analyze the behavior of the controller when there is a change in the coefficients of the valves for a transition from minimum to non-minimum phase, making use of the values from Table I. It should be noted that the test is initially configured with the hyperparameters of the non-minimal phase, because they represent the behavior that imposes the greatest difficulties, due to the cross-control actions between $v_{1j} - h_2$ and $v_{2j} - h_1$.

Figure 9 shows the graphics that define the behavior of the process. It starts in the minimum phase, adjusting the system parameters to achieve stability until the transition occurs abruptly to the non-minimum phase at 6000 seconds, as evidenced in Figures 9.c and 9.f, when p_1 passes from 0.7 to 0.35, which means that the greatest amount of water flow from pump 1 passes from tank 1 to tank 4, and finally reaches tank 2, causing the control loops to cross. The same happens with tanks 2, 3 and 1, when p_2 goes from 0.6 to 0.35.

Peaks are evident in the level of the controlled tanks, as a result of the transition that quickly achieves the stabilization of the setpoints due to the control actions. The positive peak in Figure 9.f, is due to the fact that the deviation Δp_1 = 0,35 is greater than the deviation Δp_2= 0.25, reflected in Figure 9.a with a positive stimulus and in Figure 9.d with a negative stimulus. Additionally, there is no great effort from the pumps to compensate for the abrupt change in the dynamics of the process, but rather it occurred in a controlled, gradual manner and within the normal operating parameters of the device, as shown in Figures 9.b and 9.e.

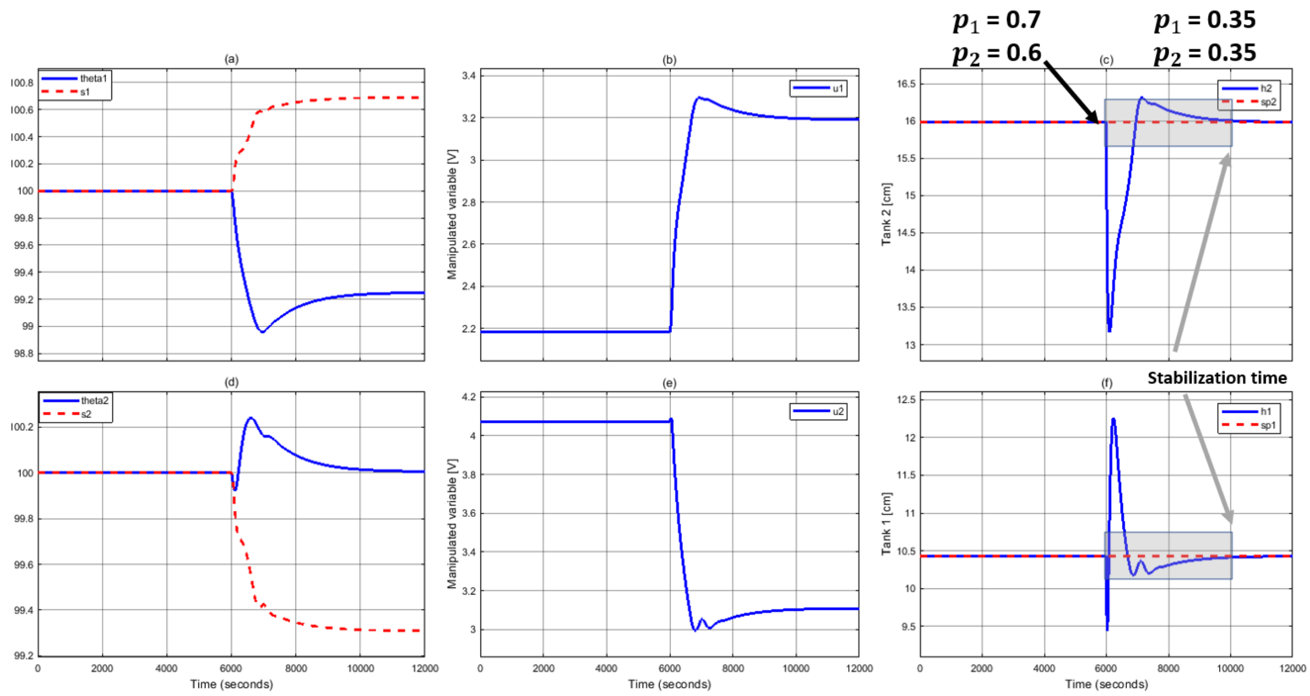


Figure 9. Process response in case study 5 - Transition between the minimum and non-minimum phase

Table IX presents the performance metrics of the controller, where it is observed in tank 2 (h_2) that the values are greater than tank 1 (h_1) due to the peak that occurs in each one, respectively. However, the stabilization times are relatively similar (see Figures 9.c and 9.f):

Table IX. Performance metrics for transition between phases

Metrics	h1	h2
ISE	14.43	42.35
IAE	16.11	29.07
ITAE	1836	3261

In most of the literature, controllers are designed to operate in a specific phase. For this reason, this operational scenario was proposed to test the performance of our emerging controller based on the response threshold; demonstrating convergence around the setpoints was achieved in both phases, as shown in Figure 9.c and 9.f.

Case study 6: Rising and falling process

The objective of this experiment is to analyze the behavior of the emergent controller in the phase of start-up and total stop of the process, establishing initial conditions at zero in all tanks and simultaneous changes in the setpoints.

Table X shows the parameters used for the experiment, where it is observed that it operates in the non-minimum phase, in addition, the level of tanks 1,2,3 and 4 are initialized at zero, to then establish a setpoint for each tank, such that it guarantees its stabilization and then returns it to 0 cm, which represents the total stop of the process. It is important to note that an initial voltage different than zero is configured to check its controlled transition in preparation for the starting process.

In Figures 10.c and 10.d, when the simulation starts, initial voltages are presented that are quickly brought to a standstill by the pumps by the action of the controller. When the instant change of the setpoints occurs, then a sudden appearance of a peak in Figure 10.c, due to the rapid change of the voltage of pump 1 in Figure 10.b to try to respond to the demand of the system. Subsequently, the setpoints are returned to zero again gradually without abrupt changes to reduce the voltage applied to the pumps to bring them to zero as well as the level of the tanks.

Table X. Initial process conditions in the case study

Parameter	**Symbol**	**No-minimum**
Valve coefficients	p_1 / p_2	0.35 / 0.35
Initial level [cm]	h_1^0 / h_2^0 / h_3^0 / h_4^0	0.0
Setpoints [cm]	h_{sp1} / h_{sp2}	16.70 / 18.1
Pump [V]	v_1^0 / v_2^0	3.1906/3.1098
Controller gain	$Gain_1 / Gain_2$	6.38 / 6.22
Initial stimulus s_i	s_1^0 / s_2^0	100 / 100
Initial response threshold θ_{ij}	$\theta_{1j} / \theta_{2j}$	100 / 100
Attenuation factor	w	0.0029

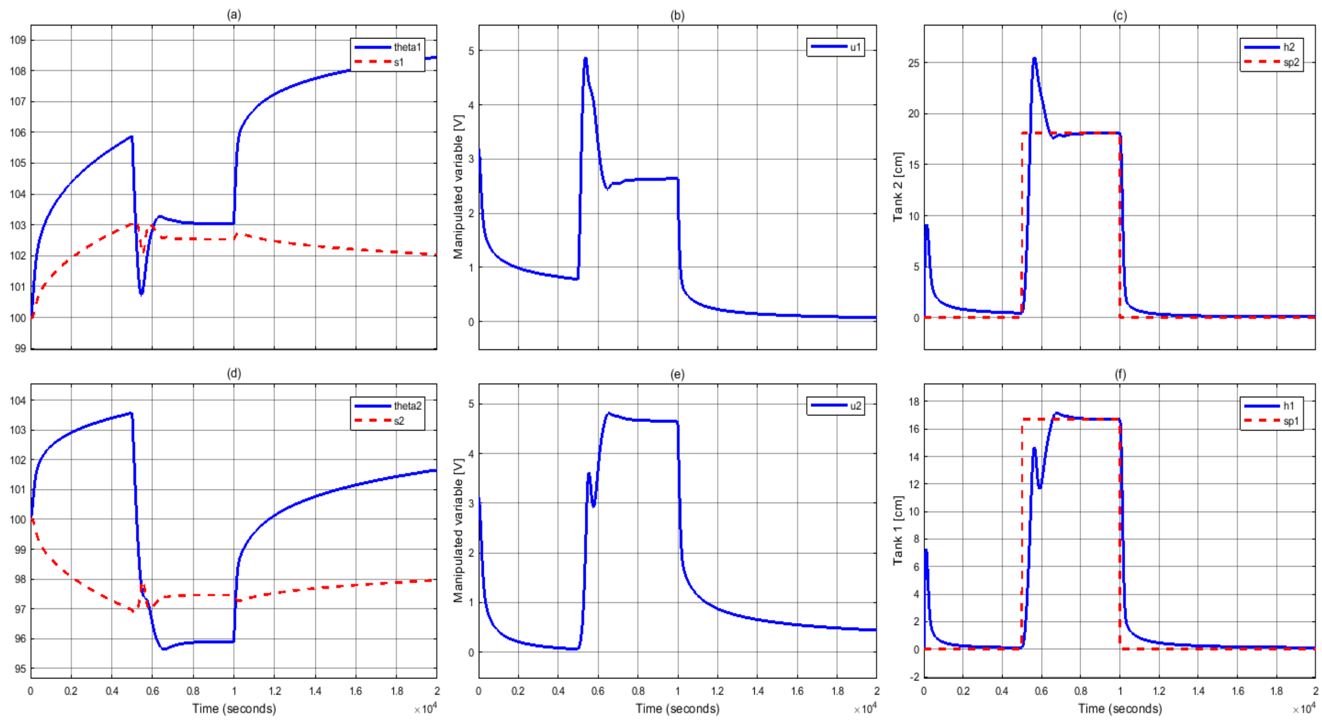


Figure 10**.** Process response in case study 6 - Rising and falling process

As presented in Table XI, it can be seen that IAE quality metrics are considerably small compared to ISE, due to the rapid convergence of tank levels to the desired values, but are penalized with sudden peaks that influence ISE.

Table XI. Performance metrics for rising and falling process

Metrics	h1	h2
ISE	2346	2549
IAE	307.60	347.00
ITAE	34445	32836

5.3 Stability analysis

Stability is one of the most important characteristics of dynamic systems and is the first objective in the design of control systems. There are several techniques to study the stability of non-linear systems, such as the Lyapunov analysis, but they are characterized by a high degree of complexity in the development of mathematical equations [24]. Reason for which, a solution will be used from the graphical point of view from the phase plane; which is a useful graphical tool for the qualitative visualization of the behavior of non-linear systems, constituted by the family of all the trajectories or solutions of a second-order non-linear system for different initial conditions. This method was introduced by Henri Poicaré [25], and is applicable to any type of non-linearity, with the premise that many systems can be approximated to a second-order one. It should be noted that for the stability analysis, the same initial conditions were considered for tanks TK-3 and TK-4 from Table I in the case of minimum and non-minimum phase, which restricts the study of the initial conditions of the controlled variables h_1 and h_2. In this sense, it remains for future work to evaluate different scenarios of the upper tanks (TK-3 and TK-4). The stability analysis of each case is presented below to determine the operating limits of the proposed emerging controller.

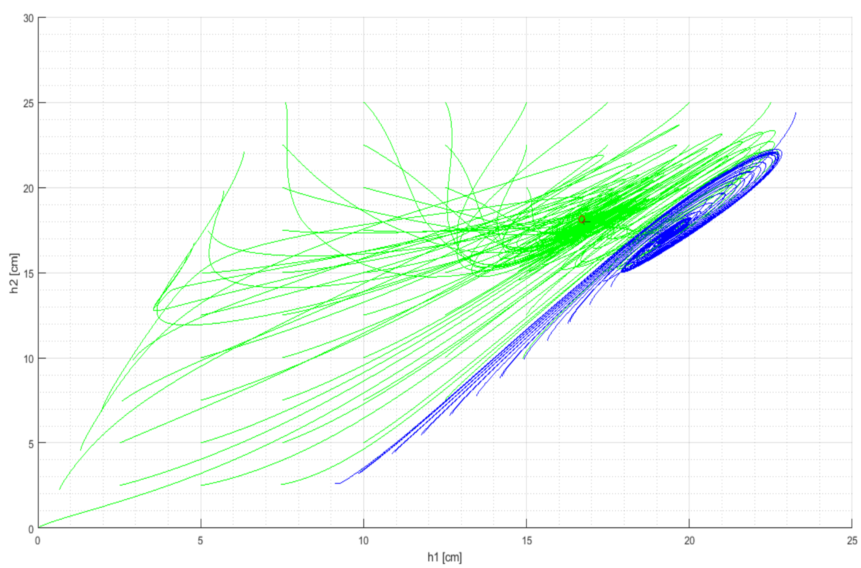


Figure 11. Phase plane portrait for minimum phase

In Figure 11, one hundred twenty-one (121) different initial conditions were sampled in the process operation domain, of which 77.69% showed convergence towards two attractors; the green lines represent the convergence path towards the setpoints (h1: 16.70 / h2: 18.1) associated with 53.72%. Also, given the nature of non-linear systems, another attractor emerges around the point (h1: 19.36 / h2: 17.22) described by the blue line, with a percentage of 23.97%. Finally, only 22.31% are zones of instability for the initial conditions represented by the blank spaces outside the traces.

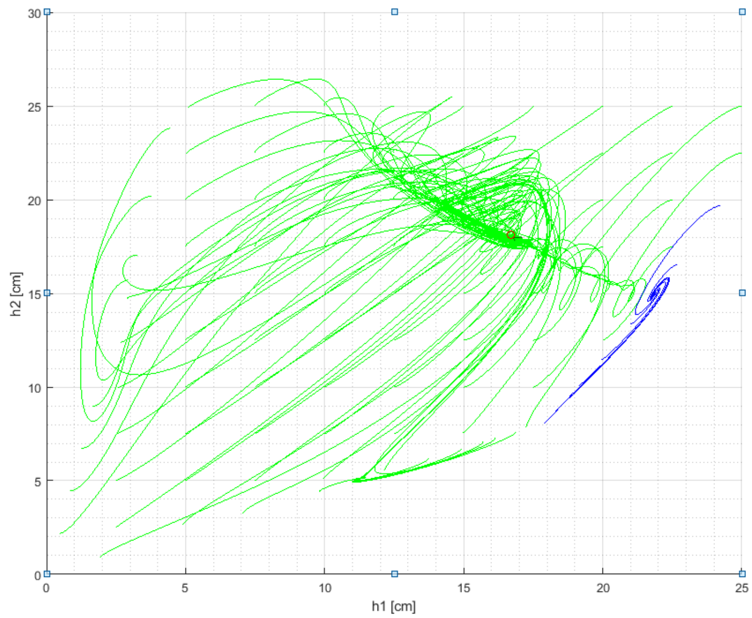


Figure 12**.** Phase plane portrait for no-minimum phase

Also, in Figure 12, the same number of initial conditions was sampled in the process operation domain, of which 81.82% showed convergence towards two attractors; the green lines represent the convergence path towards the setpoints (h_1: 16.70 / h_2: 18.1) associated with 71.90%. Again, another attractor emerged around the point (h_1: 21.85 / h_2: 14.94) described by the blue line, with a percentage of 9.92%. Finally, only 18.18% are zones of instability for the initial conditions represented by the blank spaces outside the traces.

In general, it can be observed that both phases graphically present the existence of two attractors, with a high percentage of convergence to the desired value. In the non-minimal phase, the effectiveness value is higher with 81.82%, despite the dynamics that characterize this mode of operation, which shows the stability of the proposed emergent controller.

5.4 Comparison with previous works

It is important to describe the differences between the present study in relation to similar works, highlighting the advantages and disadvantages in each case. With respect to [11], our proposal has faster times to reach the setpoint and better response to disturbances. However, in the robustness study, it was evident that for values of k less than the nominal, there is no convergence. In [13], the control problem is formulated as an optimal sequential decision problem using Markov Decision Processes (MDPs), which is solved using a combination of the Reinforcement Learning (RL) algorithm and inverse ANN controllers. They find good performance indices due to the absence of oscillations during the transition and its exploratory phase, but the dynamics of the process are slow while the interactions necessary for its learning are achieved. They also have limited test scenarios and a lack of a stability study to identify their domain of operation.

On the other hand, the controller proposed in [7] is only qualitatively analyzed, with limited metrics and test scenarios. The distributed nature was analyzed, such that each local controller takes the data from the adjacent controlled variables (level of the lower tanks), and they communicate with each other to compensate for the control actions jointly. The results regarding the performance of the transient response in [7] are good since they do not present peaks during the transition. They also lack a stability study to identify their domain of operation.

In general, it is also necessary to highlight that in the test scenarios of the works consulted during the systematic review, the transition between phases was not found. Finally, our bio-inspired approach naturally models the distributed problem, and simplifies the complexity of the control process through local actions. However, the modeling task is complex, and requires knowledge of both the bio-inspired algorithm and the process to be controlled, in order to carry out adequate parameterization. Also, our approach has the limitations inherent to the response threshold model, which are: i) It does not take into account the complex interaction networks between the components of a system (it simplifies them), ii) It assumes a single way of obtaining information (update thresholds), without considering spatial heterogeneities. Another aspect to consider is the communication cost, which refers to the transmission of remote signals between controllers to carry out control actions that contribute to error reduction, which will have a low effect if the process changes slowly, but a significant effect if the controlled variables change rapidly. Thus, contingency strategies should be taken into account in the event of a loss of communication between the controllers, among which redundancy stands out. However, currently, with the advent of new communication technologies, latency, reliability, availability and speed of communications will not be a problem.

6. CONCLUSIONS

The work proposes an emerging control scheme, where the dynamics of the process are unknown, so that the distributed control elements locally perceive the information available, to achieve the desired global control objective from their local control decisions. For this, the available local variables are the levels of the lower tanks to develop an equation that imitates the stimulus of the environment, with the purpose that each ant reacts according to it. In addition, based on the ideas of reinforcement learning, the signals that contribute to achieve the control task are grouped, creating an emergent controller based on the RTM that allows controlling the process.

A set of experiments were carried out to analyze the limitations and potentialities of the emerging controller, starting from the identification of the optimal values for the learning and forgetting factors both in the minimum and non-minimum phase, in order to reduce the error and the convergence time through the ITAE performance metric. In general, it was also observed that the intensity of the change of the setpoints affects the performance indices. Likewise, with the stability study, a convergence of 77.69% was obtained for the minimal phase and 81.82% for the non-minimal phase. Other tests were based on the rejection of external disturbances, where the robustness of the controller to unforeseen conditions that can destabilize the system was evidenced. On the other hand, controllers must be able to adapt to different devices such as pumps, where each one has its own internal parameters, the results show that the design adjusts the control actions and the nominal flow rates automatically while performing servo tracing, hence displaying robustness for values of k greater than the nominal. The tests were compared with other similar works showing better performance. Additionally, some tests were proposed to analyze the dynamics of the controller, such as the transition between phases, maintaining the convergence of the system. It is necessary to highlight the multiple test scenarios, some of them with a transition between phases, which was not found in any work reviewed during the systematic review. Finally, the paper analyzes the total start and stop of the process, taking as a reference the null levels of the tanks, being also satisfactory.

For future work, it is proposed to adapt the hyperparameters like learning rate, forgetting rate, attenuation factor and controller gain in real-time to improve the response of the system, since this process was carried out at the beginning to find the initial optimal point of operation. Also, coefficients of the valves can be dynamically established in the controllers, by the relationship between tanks and pump flows to achieve the assignment of tasks in more complex processes and with a greater number of variables. Another study will analyze the communication cost caused by the delay of the signals due to the distance between the controllers. Also, a work will study the stability of the process in different scenarios of the upper tanks (TK-3 and TK-4). Finally, the application of our emergent control could be extended to other distributed case studies in order to systematize the implementation process.

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