Доклади на Българската академия на науките
Comptes rendus de l'Académie bulgare des Sciences

Tome 78, No 6, 2025

ENGINEERING SCIENCES

Artificial intelligence

ADAPTIVE CONTROL OF PYROLYSIS REACTOR'S TEMPERATURE MODES BASED ON FUZZY LOGIC AND METAHEURISTIC OPTIMIZATION

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Received on February 3, 2025
Presented by K. Atanassov, Member of BAS, on April 29, 2025

Abstract

This article introduces and validates an advanced approach to adaptive automatic control of pyrolysis reactors, aimed at optimizing the utilization of agricultural plastics. By integrating fuzzy logic with enhanced metaheuristic optimization technique, the proposed method achieves superior performance in regulating reactor temperature modes. A key feature of this approach is the incorporation of the reactor's current loading level as an additional variable in the antecedents of the adaptive fuzzy controller's rule base. This dynamic adaptation is further enhanced through the application of the hybrid improved gray wolf optimization algorithm, which optimizes the rule base parameters to increase the robustness and accuracy of control. To assess the effectiveness of this methodology, a fuzzy control system was designed for a specific pyrolysis reactor. Simulation results confirm the approach's superiority over traditional controllers in response speed, accuracy and robustness in various operating conditions. In particular, at a reactor loading level of 100% at startup of the installation and subsequent transition to steady-state operation, the application of the proposed approach made it possible to reduce the transient process duration by 2.26 times and decrease in overshoot by 48.4% compared to existing

This study is financially supported by the National High Level Foreign Experts Introduction Project, China (G2022014116L). We thank the Introduction of Intelligence Projects for Policy Guidance in Yancheng (YCBX2022005) and Scientific Research Project of Yancheng Polytechnic College (ygy2103).

`https://doi.org/10.7546/CRABS.2025.06.11`

systems. This, in turn, will lead to a reduction in molecular weight fluctuations and an improvement in the quality of the resulting fuel fractions, thereby significantly enhancing the general energy efficiency and economic performance of agricultural enterprises utilizing pyrolysis technologies.

Key words: agricultural plastics utilization, pyrolysis reactor, temperature modes control system, adaptive fuzzy controller, gray wolf optimization

Introduction. The extensive use of agricultural plastics, such as mulching films, irrigation components, and greenhouse covers, enhances productivity but poses disposal challenges [1]. Conventional methods like incineration and landfilling contribute to pollution, raising environmental concerns [2]. Pyrolysis, a thermochemical process in an oxygen-deprived environment, provides a sustainable alternative by converting plastic waste into liquid fuel, syngas, and char [3,4]. This process reduces plastic pollution while generating valuable byproducts for energy and industry, making it a key element of sustainable waste management. On the other hand, the effective implementation of pyrolysis for agricultural plastics requires highly automated multi-loop circulating plants and advanced control systems for economic and energy efficiency [5]. These systems must precisely stabilize process variables to ensure high-quality fuel fractions. Given the complexity of pyrolysis plants, particularly their reactors, which are objects with nonlinear and non-stationary parameters, the application of intelligent control principles is essential. In particular, systems based on fuzzy logic developed to date have demonstrated enough good effectiveness in controlling various types of pyrolysis plants, including fuzzy PID [6], self-tuning [7], combined [5], and predictive [8] algorithms. By adeptly generalizing expert knowledge and experimental data, and approximating complex, difficult-to-formalize dependencies, modern fuzzy systems achieve superior performance in controlling various intricate technical processes [9–11].

Despite significant advancements in the field and the results obtained in the above works, a key challenge remains unresolved: improving reactor temperature control under significant parameter changes. Among various disturbances, stemming from physical and chemical processes during the hydrocarbons thermal decomposition, a change in the reactor loading level has the greatest impact, altering its dynamic characteristics and disrupting temperature regulation. Such variability can compromise the accuracy of the considered fuzzy control systems, despite their inherent robustness. Even slight deviations from the target temperature affect product molecular weight, degrading fuel quality. This type of significant parametric disturbance is not specifically taken into account in the reviewed studies, which highlights the critical need for creating more adaptive and precise control strategies to ensure optimal reactor performance.

To solve the outlined challenge, this paper proposes an innovative approach to reactors' adaptive fuzzy control by incorporating an additional variable into the rule base (RB) antecedents, which accounts for a change in reactor loading level. The creation of a new RB, enhanced with this variable, is implemented by using an advanced metaheuristic search method, specifically the hybrid improved gray wolf optimization (HIGWO) algorithm. Hence, the central aim of this study is to develop and validate an advanced approach to adaptive automatic control of pyrolysis reactor temperature modes, leveraging the synergy of fuzzy logic and HIGWO to improve the accuracy and response speed of the system under parametric disturbances.

Proposed methodology. The implementation of the proposed approach for adaptive fuzzy control of a pyrolysis reactor encompasses three primary stages: 1) designing the structure of the adaptive temperature control system, taking into account changes in the reactor's loading level; 2) developing an adaptive fuzzy controller for precise reactor temperature regulation; and 3) synthesizing the parameters of the fuzzy controller for a specific pyrolysis reactor through the HIGWO-based optimization of the consequents' coefficients in the RB. Additionally, the application of this approach requires the utilization of a mathematical model of the pyrolysis reactor as a temperature control object, constructed from experimental data as detailed in [12].

Pyrolysis reactor's mathematical model. Specifically, this model represents the transfer function $W_{\mathrm{R}}(s)$ along the control channel [12], featuring variable parameters

$$W_{\mathrm{R}}(s) = \frac{T_{\mathrm{R}}(s)}{P_{\mathrm{GB}}(s)} = \frac{K_{\mathrm{R}} e^{-\tau_{\mathrm{R3}} s}}{(\tau_{\mathrm{R1}} s + 1)(\tau_{\mathrm{R2}} s + 1)^2}.$$

In this context, the transfer function input P_{GB} is the gas burner's heating power, while the output T_{R} corresponds to the reactor's temperature at the control point. The gain K_{R} and time coefficients τ_{R1}, τ_{R2}, τ_{R3} of the transfer function change depending on the reactor's loading level L_{R} and the P_{GB} value, based on the nonlinear dependencies, which are derived through identification, utilizing experimental data, and subsequently approximated using specially developed fuzzy models [12]. In turn, the transients were obtained for reactors of different volumes, operating under various modes and processing diverse raw materials.

Structure of the adaptive temperature control system. The reactor's temperature control system, designed to implement the proposed adaptive approach, should be structured as illustrated in Fig. 1. In turn, Fig. 1 utilizes the following notations: HO is a system's human operator; MSU is the mode setting unit; AFC is the adaptive fuzzy controller; TS is the temperature sensor; LS is the level sensor (non-contact); GB is the automatic gas burner that allows to operate simultaneously on natural gas (NG) and released pyrolysis gas (PG) with the determination of the optimal air (A) consumption; SOU is the synthesis and optimization unit for the AFC tuning; PW are the polymer wastes that are fed into the reactor for thermal utilization; LF and SR are the liquid fractions of fuel and solid residue; T_{R} and L_{R} are the current values of the reactor's heating temperature and loading level; P_{GB} is the heating power of the GB; u_{TS}, u_{LS},

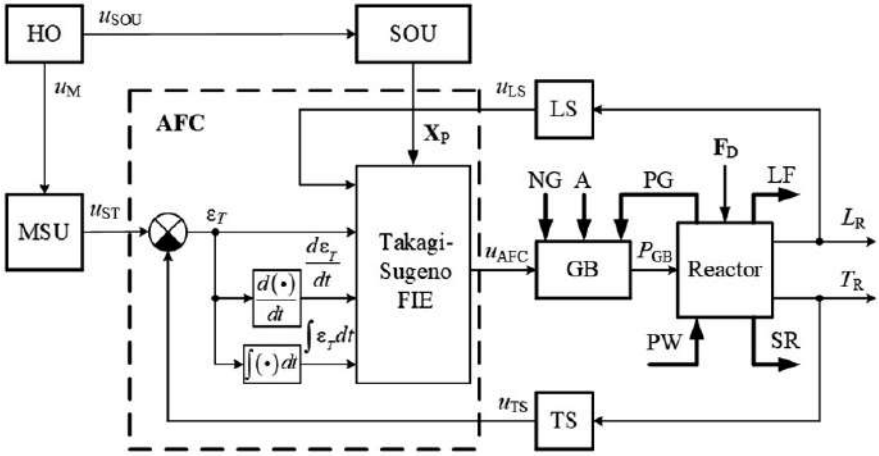

Fig. 1. Structure of the adaptive control system for the reactor's temperature modes

and u_{AFC} are the corresponding output signals of the TS, LS, and AFC; u_{ST} is the signal corresponding to the desired temperature value; u_{M} is the signal that determines the required temperature mode; $\mathbf{X}_{\mathrm{P}}$ is the vector of parameters found by the SOU that are subsequently set into the AFC; u_{SOU} is the parameter setting signal for the SOU; ε_T is the temperature control error; $\mathbf{F}_{\mathrm{D}}$ is the disturbances vector acting on the reactor.

In this system, the HO specifies the desired temperature regime based on the type of waste processed in the reactor and configures the SOU for subsequent optimization of the AFC. In turn, the primary objective of the AFC is to precisely stabilize the prescribed temperature mode, accommodating changes in the current loading level.

Adaptive fuzzy controller. This system advocates employing an adaptive temperature controller utilizing a Takagi–Sugeno fuzzy inference engine (FIE). The controller's inputs include the signal u_{LS} corresponding to reactor loading level L_{R}, temperature control error ε_T, along with its derivative $d\varepsilon_T/dt$ and integral $\int \varepsilon_T\,dt$. For these controller inputs, the given sets of linguistic terms (LT) are selected (Table 1).

Table 1

Linguistic terms of the AFC

Input	Number of LTs	Selected LTs	Membership function	Operating range
u_{LS}	3	Low (L); Medium (M); High (H)	triangular	$[0;1]$
ε_T	5	Big negative (BN); Small negative (SN); Zero (Z); Small positive (SP); Big positive (BP)	triangular	$[-1;1]$
$d\varepsilon_T/dt$	3	Negative (N); Zero (Z); Positive (P)	triangular	$[-1;1]$
$\int \varepsilon_T\,dt$	3	Negative (N); Zero (Z); Positive (P)	triangular	$[-1;1]$

The parameters of these terms are set in relative units (from maximum values) and evenly distributed across their operating ranges. The rule base of the adaptive controller comprises 135 rules, encompassing all possible combinations of the input variables, including an additional variable that characterizes the reactor's loading level. Each r-th rule ($r = 1, 2, \ldots, 135$) within this base adheres to the following general structure:

$$\begin{gathered}\text{IF “}u_{\mathrm{LS}} = LT_{1r}\text{” AND “}\varepsilon_T = LT_{2r}\text{” AND “}d\varepsilon_T/dt = LT_{3r}\text{”} \\ \text{AND “}\textstyle\int \varepsilon_T\, dt = LT_{4r}\text{”} \\ \text{THEN “}u_{\mathrm{AFC}} = k_{\varepsilon r}\varepsilon_T + k_{d\varepsilon r}\, d\varepsilon_T/dt + k_{I\varepsilon r}\textstyle\int \varepsilon_T\, dt\text{”,}\end{gathered}$$

where LT_{1r}, LT_{2r}, LT_{3r}, LT_{4r} are the selected LTs of the corresponding inputs; $k_{\varepsilon r}$, $k_{d\varepsilon r}$, $k_{I\varepsilon r}$ are the consequents' weight coefficients of the corresponding r-th rule of the RB.

In this case, the primary objective of synthesizing the proposed controller is to determine the optimal values for the weighting gains of the consequents across all 135 rules. These values should ensure superior performance in adaptive temperature control, particularly in response to variations in the reactor's loading level. In turn, the vector $\mathbf{X}_{\mathrm{P}}$ comprises 405 coefficients that need to be determined by means of the SOU. To achieve this, the proposed approach recommends employing the HIGWO algorithm [13].

Hybrid improved gray wolf optimization algorithm. The HIGWO algorithm has demonstrated significant efficacy in developing various fuzzy systems for complex technical objects [13]. It incorporates the cooperative hunting strategy of the standard GWO while introducing an additional dimension learning-based hunting mechanism to enhance population diversity. Furthermore, a parallel local search strategy is employed to accelerate convergence toward the global optimal solution. To achieve this, the three best agents in the population (alpha, beta, and delta) execute a parallel search at each iteration using the Extended Kalman Filter algorithm. All the peculiarities and primary steps of this algorithm are comprehensively detailed in [13]. In this case, the weight coefficients comprising vector $\mathbf{X}_{\mathrm{P}}$ serve as the dynamic positional coordinates of the population agents during the optimization search process. The objective function J, employed to assess the quality of the reactor temperature control in dynamic modes, is defined as the generalized integral quadratic deviation between the reference model output, $T_{\mathrm{D}}(t)$, and the actual reactor temperature, $T_{\mathrm{R}}(t, \mathbf{X}_{\mathrm{P}})$:

$$J(t, \mathbf{X}_{\mathrm{P}}) = \frac{1}{t_{\max}} \int_0^{t_{\max}} [(E_T)^2 + k_{J1}(\dot{E}_T)^2 + k_{J2}(\ddot{E}_T)^2]\, dt,$$

where $t_{\max}$ denotes the total regulation time; k_{J1}, k_{J2} represent the weighting coefficients of the function J; the deviation $E_T = T_{\mathrm{D}}(t) - T_{\mathrm{R}}(t, \mathbf{X}_{\mathrm{P}})$.

Results and discussions. The proposed approach was validated through its application to control the temperature modes of a specific 100-liter reactor of the experimental pyrolysis facility designed for polyethylene processing. The gas burner with a maximum heating power of 25 kW was used. During the implementation of the HIGWO algorithm, the population size was set to 30 agents, with the termination criterion for the optimization process defined as reaching 200 iterations. To ensure the accurate synthesis of the consequent coefficients for all controller rules, the system was simulated across all potential operating conditions when evaluating the objective function at each iteration. Specifically, the modelling encompassed scenarios involving the reactor's initial heating at different loading level, subsequent level reduction during waste disposal, and the presence of diverse disturbances.

Given the stochastic nature of the algorithm, the optimization process was executed five independent times. The most favourable results obtained from these iterations were subsequently selected for further controller's operation. As a result, a complete RB with optimized consequents coefficients of all 135 rules was successfully synthesized.

Moreover, for a comprehensive analysis, alongside the proposed AFC, two additional controllers were synthesized: a Takagi–Sugeno conventional fuzzy controller (CFC) that does not account for variations in the reactor loading level (utilizing three inputs: temperature error ε_T, its derivative, and its integral), and a conventional linear proportional-differential-integral (PID) controller. To ensure an objective comparison, the parameters of these controllers were also optimized using the HIGWO algorithm.

The results of core research and the simulation experiments are presented in Fig. 2 and analyzed below. In this case, each of the six graphs shows separate comparisons of the efficiency of the three studied controllers in various operating conditions of the system (the AFC is presented by a solid line, the conventional fuzzy and PID controllers are presented by various dotted lines, as shown at the bottom of Fig. 2). In particular, graphs *a*, *b*, *c* show the transient process of the system at the initial start-up with different levels of reactor loading, and graphs *d*, *e*, *f* – the system's response at the operating point under the action of coordinate and parametric disturbances (a sharp step drop in temperature and an increase in the reactor loading level by different percentages). Therefore, for greater clarity and convenience of analyzing the quality of transient processes, graphs *d*, *e*, *f* are detailed.

Thus, the adaptive control system for the reactor, developed using the proposed AFC, exhibits markedly superior control performance and robustness compared to systems utilizing a conventional fuzzy controller with three inputs and a traditional PID controller. During the initial heating phase of the reactor (Fig. 2*a*, *b*, *c*), under varying initial loading levels of 20%, 50%, and 100%, and throughout the gradual decrease in level during the utilization process, the adaptive system achieves significantly reduced transient time and overshoot. Specifically, at a loading level of 100% in response to a step control signal, the transient time is reduced

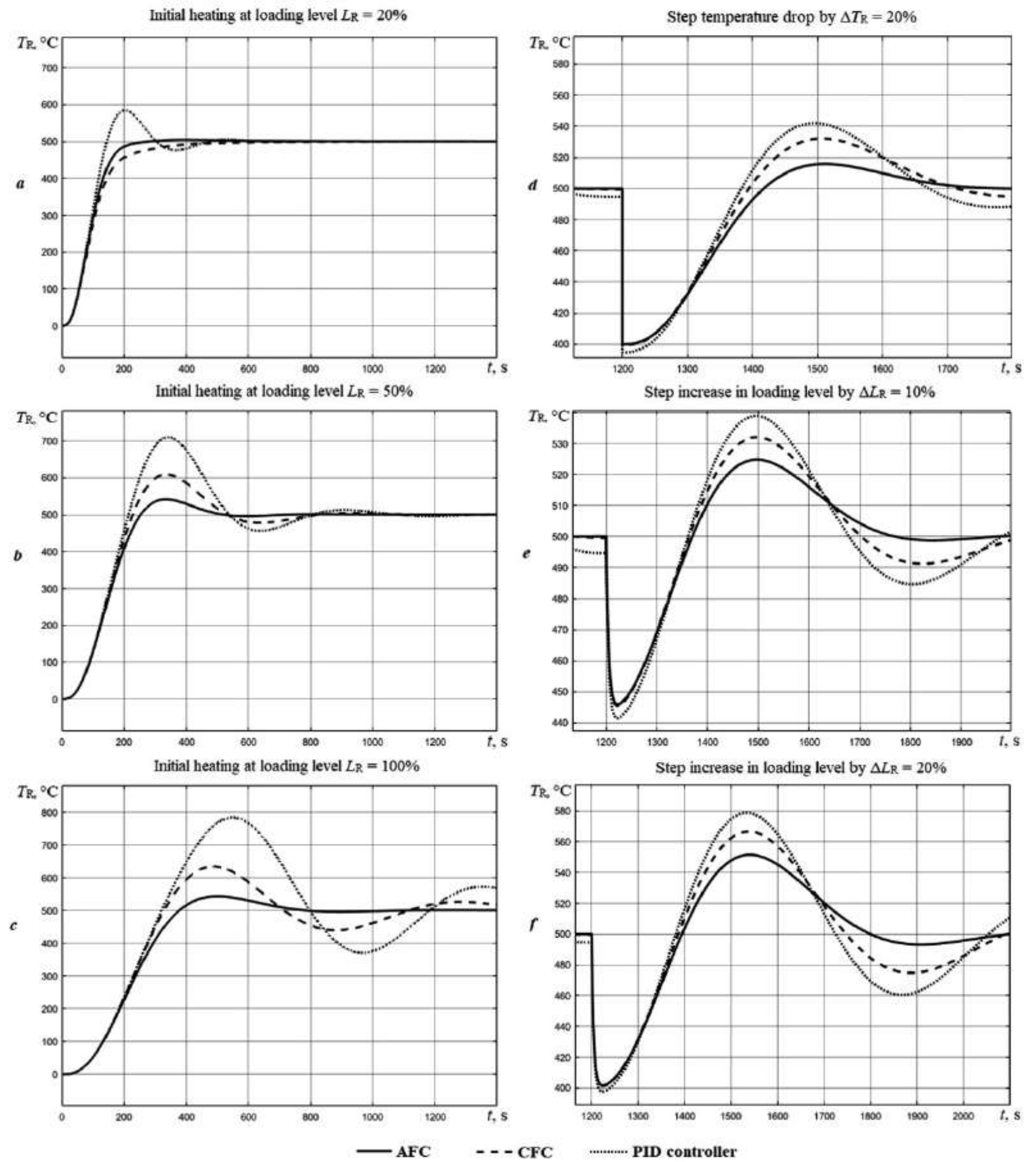

Fig. 2. Transients of the reactor's temperature control at a set value of 500 °C: a, b, c – initial heating when the system starts; d, e, f – system response to step disturbances (at $L_R = 80\%$)

by 1.91 times compared to the three-input CFC-based system and by 2.26 times compared to the PID-based system.

Additionally, the maximum overshoot is lower by 19.2% and 48.4%, respectively. Similarly, in response to step disturbances at 1200 s (Fig. 2d, e, f), the AFC demonstrates shorter transient time, reduced overshoot, and enhanced robustness. For instance, when the load level abruptly increases by 20%, the recovery time is reduced by 267 s and 384 s, respectively.

The conducted studies have demonstrated that the advanced approach employed for optimizing the AFC facilitated its effective adaptation to significant variations in reactor loading level, while also enhancing its robust performance characteristics. This advancement substantially improves the precision of temperature regulation, thereby ensuring a higher quality of the resulting output products. These findings unequivocally confirm the high efficacy of the proposed approach and underscore its practical feasibility for implementation in the control systems of pyrolysis plants, both within agricultural applications and across other industrial sectors.

Conclusions. The proposed approach based on fuzzy logic and metaheuristic optimization achieves exceptional performance in regulating the reactor's temperature modes, which markedly enhances the quality of the resulting output fractions. This improvement is realized through the incorporation of the reactor's current loading level as an additional variable in the antecedents of the adaptive fuzzy controller's RB, along with the subsequent optimization of this rule base using the HIGWO algorithm.

To evaluate the effectiveness the fuzzy control system was developed for the specific pyrolysis reactor. Simulation results demonstrate that the AFC significantly outperforms conventional three-input fuzzy and linear PID controllers in achieving accurate and robust temperature regulation under dynamic operating conditions. The enhanced accuracy and stability of temperature control, even under significant loading level changes, will reduce fluctuations in the molecular weight of output fuel fractions, thereby improving product quality. This confirms the high efficiency of the approach and its applicability to pyrolysis plants of various types and capacities in the agricultural sector. As a result, the improved efficiency of polymer waste recycling processes and the quality of resulting products can greatly enhance the energy and economic performance of agricultural enterprises employing pyrolysis technologies.

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