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Fuzzy Control Model with Automated Rule Base Generation for Artillery Systems in Game Simulators

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Abstract

This paper presents the development and validation of a fuzzy control model with automated rule base generation for artillery system actuators in game simulators. The proposed model integrates a bioinspired optimization mechanism based on the ant colony algorithm, enabling the automatic synthesis of efficient rule bases without relying on expert knowledge. This approach ensures adaptability and autonomy under uncertain conditions and provides logical transparency, allowing detailed analysis of control strategies. The model can be employed to simulate the decision-making behavior of virtual allies or adversaries, representing their different skill levels by adjusting reference models and objective functions at the design stage, thereby enhancing the realism in combat scenarios simulation. Experimental studies conducted on the example of an electric drive simulation model responsible for artillery mount barrel elevation demonstrated the superiority of the fuzzy model over a traditional PD controller in terms of robustness, efficiency and accuracy. The methodology presented in this paper can also be applied to hydraulic and other types of actuators.

Keywords: game simulators; artillery systems; fuzzy control model; rule base generation; actuator model.

1. Introduction

In the context of twenty-first century warfare, the rapid proliferation of unmanned aerial vehicles (UAVs) has profoundly transformed reconnaissance, surveillance, and precision strike capabilities. Nevertheless, artillery continues to occupy a central role as one of the most decisive instruments of firepower on the battlefield [1]. Its capacity to deliver sustained, large-scale, and comparatively cost-effective destructive force ensures that it remains indispensable for neutralizing enemy positions, disrupting logistical lines, and providing both offensive and defensive support. Unlike UAVs, which often depend on sophisticated communication infrastructures and are vulnerable to electronic countermeasures, artillery systems maintain their relevance through robustness, operational reliability, and their ability to operate effectively in a wide range of tactical and operational conditions [2].

At the same time, modern high-intensity, technologically advanced combat environments impose exacting demands on artillery employment that transcend traditional paradigms of massed fire [3]. Contemporary operations require pinpoint engagement of threat elements with minimal ammunition expenditure, a significant reduction in time-to-target and in the duration of exposure within firing positions, and the capacity to sustain high sortie rates under contested, degraded conditions. These operational imperatives, compounded by accelerated fatigue and premature wear of mechanical, electromechanical, and electronic subsystems, render conventional, manually tuned

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procedures insufficient. Accordingly, there is an urgent need for novel algorithmic frameworks and mathematical models that provide real-time control, adaptive correction, and predictive diagnostics at multiple hierarchical levels: from sensors, actuators, and individual weapon components to coordinated fire units, batteries, and integrated fire-support systems. Such methods must reconcile stringent constraints on lethality, survivability, and logistical economy while enabling autonomous or semi-autonomous decision-support that is robust to uncertainty, component degradation, and adversarial interference.

A similar tendency can be observed in the field of game simulators development [4]. The demand for achieving maximum realism in the operation of combat vehicles, including artillery systems, under complex and rapidly changing conditions necessitates the application of sophisticated mathematical models and control algorithms. Conventional simplified approaches are no longer adequate to capture the dynamic and uncertain nature of modern battlefield processes. At the same time, the growing role of training, decision support, and operational analysis within virtual environments increases the requirements for accuracy, adaptability, and intelligence in simulation models. In this context, the application of intelligent control models and techniques, encompassing adaptive, data-driven and knowledge-based approaches, emerges as one of the most promising directions [5]. The search for effective approaches to building such models, particularly those based on fuzzy logic and capable of generating and refining rule bases, constitutes the subject of the present study.

2. Literature sources analysis

Contemporary scientific research offers a wide spectrum of advanced computational approaches, mathematical models, and information technologies designed to enhance the precision of artillery fire, improve the prediction of projectile trajectories, and increase the overall reliability of operation, alongside other critical performance characteristics of artillery systems [6], [7]. At the same time, considerable progress has been achieved in the field of verification methodologies, which now make it possible to assess and diagnose the required properties of virtually all essential subsystems of artillery mounts and complexes, ranging from projectiles, charges, and munitions to the supporting logistical infrastructures, across every crucial stage of their life cycle [8], [9]. Furthermore, a significant portion of these methods and models has found successful application in the domain of game-based simulation, where they serve to improve realism and fidelity of virtual representations of artillery processes [10] – [12].

For example, the article [10] examines the tactical use of artillery in counter-amphibious operations across both deep- and shallow-water conditions, with a focus on game-based scenario modeling. Using mathematical models grounded in Markov chains and complementary simulation techniques, the study explores the balance between sustained fire support, resource efficiency, and artillery survivability. Several tactical approaches are analyzed, including ammunition-saving strategies, rapid neutralization methods, and hybrid solutions that adapt to specific battlefield conditions. The results demonstrate the advantages of the mixed method, which ensures operational flexibility and higher effectiveness in countering amphibious assaults.

In turn, the study [11] addresses the critical issue of artillery ammunition quality in modern warfare, with insights drawn from recent conflict experiences. The study develops optimized acceptance sampling algorithms that balance inspection efficiency, resource constraints, and operational reliability, taking into account the impracticality of full inspection. By tailoring sampling plans to different types of artillery missions, the approach ensures both high-quality munitions for destructive fire and efficient use of resources for suppressive operations. The results demonstrate that such strategies not only enhance safety and readiness in real combat but can also be effectively integrated into game-based simulations for greater realism.

The work [12] explores the gap between visual realism and limited scripting in military-themed computer games, focusing on artillery modeling in ARMA 3. The study introduces a shot verification method based on recording projectile flight times at control points and constructing parabolic approximations to predict impact accuracy. Simulation results show that this approach effectively compensates for random disturbances, reducing firing time and ammunition use compared to traditional ranging shots. The findings highlight the potential of integrating advanced artillery verification methods into game simulators for enhanced realism and tactical depth.

At the same time, modern scientific literature devotes comparatively little attention to a rather specific yet critical problem, namely, the control of individual actuators in artillery mounts to ensure precise aiming under the influence of uncertain and variable disturbances. Intensive operational regimes, premature wear, mechanical defects, and environmental factors such as overheating, strong winds, or electromagnetic interference can all lead to significant variations in drive parameters. These fluctuations undermine the effectiveness of conventional control systems with rigidly defined settings, ultimately reducing the accuracy and speed of barrel guidance. The resulting degradation manifests in longer mission execution times, prolonged exposure in firing positions, and increased probable circular error. To address these challenges, a number of studies have proposed the application of fuzzy control models, which have demonstrated the ability to improve both precision and responsiveness of aiming mechanisms [13] – [15]. This methodology also holds considerable promise for game simulators, as the mathematical apparatus of fuzzy logic provides a means of emulating human reasoning and integrating experiential knowledge into the operation of a virtual ally or adversary.

Nevertheless, the issue of generating a reliable fuzzy rule base remains largely unresolved: expert knowledge is not always available, its correct application may be limited, and manual rule formulation is susceptible to subjective bias and errors. In light of this, the present paper proposes an automated approach to rule base generation using a bioinspired optimization algorithm for the fuzzy control models of artillery systems' actuators in game simulators. Such a solution enables the simulator to emulate the presence of an experienced operator, while the ability to adjust the optimization objective function further allows the modeling of varying skill levels of virtual counterparts.

3. Objective and tasks of the research

The central objective of this research is the development of a fuzzy control model with automated rule base generation for the artillery systems' actuators within game simulation environments. In pursuit of this objective, the study sets out to address several key tasks: 1) the conceptual design of the fuzzy control model's structure; 2) the creation of an automated mechanism for rule base formation utilizing a bioinspired optimization algorithm; and 3) the experimental validation and performance assessment of the proposed fuzzy control model.

4. Model and methods

Basic aspects of constructing a fuzzy control model for artillery mount actuators. The principal tasks amenable to resolution with the proposed fuzzy-control architecture are the closed-loop regulation of gun-barrel elevation and the precise steering of azimuth during target engagement. To enact automatic regulation of either angular degree of freedom, the controller must be supplied with a commanded setpoint (e.g., desired elevation) and the corresponding instantaneous feedback measurement. The demanded setpoint is ordinarily computed by the fire-control subsystem on the basis of embedded ballistic models, which obtain target coordinates, the current emplacement position, atmospheric and environmental data, and other mission-relevant inputs. The actual angular state in physical mounts is obtained from position transducers (encoders, resolvers, etc.), whereas in a game simulation environment it is produced by the simulation model of the studied drive.

For generation of the control signal, the fuzzy regulator model operates on the angular error (the difference between commanded and measured angle) and on selected time derivatives or integrals of that error. A review of typical barrel-drive dynamics shows that these subsystems behave as non-self-stabilizing, predominantly integrating plants. Accordingly, effective closed-loop performance can be achieved using the error and its first time derivative alone. Introducing the error integral as an additional input seldom yields commensurate gains in positioning accuracy for such integrating objects, yet it can create undesirable phenomena – most notably integrator windup and degraded transient stability – unless additional anti-windup measures are implemented. Likewise, inclusion of higher-order derivatives amplifies sensitivity to measurement noise and imposes onerous requirements on filtering and signal conditioning. Therefore, a parsimonious input set comprising the angular error and its first derivative provides a pragmatic balance between control precision and robustness for both physical installations and their simulator counterparts. Therefore, the chosen control architecture will achieve significant efficiency and is quite simple to implement.

For the fuzzy inference engine, the Mamdani approach is the most appropriate choice, as it provides a high degree of interpretability and logical transparency [16]. This property is particularly valuable in game simulation environments, where clarity of decision-making is essential for modeling the behavior of virtual allies and adversaries. The Mamdani inference enables the construction of an explicit rule base expressed in the familiar "If–Then" format, where the consequents are formulated in terms of linguistic values assigned to the output variable. For example, for a model of fuzzy control of the barrel elevation angle φ, the rules of the rule base can be defined as follows:

$$\text{IF “}\varepsilon_{\varphi} = A_i\text{” AND “}\frac{d\varepsilon_{\varphi}}{dt} = B_j\text{” THEN “}u_{\varphi} = C_k\text{”,} \tag{1}$$

where ε_φ is the angle φ control error; u_φ is the calculated control signal; A_i is the i-th linguistic term from the set of terms for control error ε_φ, $i \in \{1,...,i_{\max}\}$; B_j is the j-th linguistic term from the set of terms for error's derivative $d\varepsilon_\varphi/dt$, $j \in \{1,...,j_{\max}\}$; C_k is the k-th linguistic term from the set of terms for control signal u_φ, $k \in \{1,...,k_{\max}\}$.

In this scheme, the number of rules and the structure of their antecedents are determined by the chosen linguistic partitions (the numbers i_{max} and j_{max}) of the input variables, namely, the control error ε_φ and its time derivative $d\varepsilon_\varphi/dt$ [16]. These partitions can be defined at the initial design stage, which makes the subsequent formulation of the rule base a matter of assigning the most appropriate consequent to each input combination. The diversity of possible consequents depends directly on the number of linguistic terms k_{max} introduced for the output variable u_φ, also specified in advance. A finer partitioning with a larger number of terms yields greater flexibility and the potential for more sophisticated control strategies. However, it also increases the computational burden and complicates the synthesis process. Conversely, a minimal set of terms simplifies both design and implementation but limits smoothness and adaptability in control responses. Thus, effective model construction requires a balanced compromise, ensuring sufficient expressiveness without imposing excessive complexity on the rule base and its real-time execution.

For the automated synthesis of a fuzzy rule base, the generation mechanism must incorporate several essential stages: 1) the initial creation of the rules antecedents, 2) the assignment of valid consequents to every generated rule, and 3) the evaluation of the correctness and efficiency of the constructed rule base. The formation of the rules antecedents at the first stage can be performed in a straightforward manner by systematically enumerating all possible combinations of the linguistic terms selected for the input variables during the preliminary design phase [16].

The more challenging task lies in assigning suitable consequents to each rule. This can be formulated as a discrete optimization problem, where the set of consequents constitutes the vector of parameters to be optimized [16]. To solve this problem effectively, it is proposed to employ a computationally efficient bioinspired optimization algorithm, capable of navigating the discrete solution space and identifying the most appropriate consequents [17].

The quality of the resulting rule base must then be rigorously evaluated. This requires the definition of an objective function that quantifies the proximity of the control performance obtained from the fuzzy model to the desired performance characteristics. To ensure a comprehensive assessment, it is advisable to compare the examined control system with a reference model, which embodies the target properties such as accuracy, response speed, and stability. The chosen objective function simultaneously serves as a fitness function within the optimization process, being evaluated at each iteration of the bioinspired algorithm. Consequently, once the algorithm converges to a predefined optimal value of this fitness function, the synthesized rule base can be considered sufficiently effective, containing the most appropriate consequents for all generated rules [17].

Building upon the considerations outlined above, it is now possible to address the first key task of this research, namely the development of structure for the fuzzy control model intended for the actuators of artillery mounts.

Structure of the fuzzy control model for artillery mount actuators. Fig. 1 illustrates the structural framework of the fuzzy control model with automated rule base generation for artillery system actuators. The adopted designations and symbols are explained as follows: FCM is the fuzzy control model; FB is the fuzzification block; RB is the rule base; DFB is the defuzzification block; FIB is the fuzzy inference block; AGG, ACT, and ACC are the operators that perform aggregation, activation and accumulation procedures, respectively; MARBG is the mechanism of automated rule base generation; AGB is the antecedents generation block; CGB is the consequents generation block; RM is the reference model; OFCB is the objective function calculation block; BOA is the bioinspired optimization algorithm; SMAAM is the simulation model of the actuator of the artillery mount; DMB is the disturbance modeling block; φ_d and φ_c are the desired and current values of the actuator lifting (rotation) angle; ε_φ is the angle control error; $d\varepsilon_\varphi/dt$ is the error's derivative; u_φ is the FCM output signal; $\mathbf{A}_\varepsilon$, $\mathbf{B}_{d\varepsilon}$, and $\mathbf{C}_u$ are the vectors of linguistic terms used for the variables ε_φ, $d\varepsilon_\varphi/dt$, and u_φ, respectively; $\mathbf{X}_A$ and $\mathbf{X}_C$ are the vectors of RB antecedents and consequents; φ_m is the RM output; E_φ is the mismatch between the output of the reference model and the current value of the angle ($E_\varphi = \varphi_m - \varphi_c$); J_φ is the value of the objective function; $\mathbf{\Delta P}$ is the vector of changes in the parameters of the actuator model under the action of parametric disturbances; $\Delta\varphi$ is the change in angle under the action of coordinate disturbances.

In this framework, different types of actuator models, such as electric, hydraulic, or electrohydraulic drives, can be employed as SMAAM, each with its own degree of detail and complexity, depending on the fidelity required in the game simulator environments. To simplify the representation of external and internal disturbances, a dedicated DMB is incorporated. This block enables the emulation of various forms of uncertainty, ranging from parametric variations (vector $\mathbf{\Delta P}$) to fluctuations in the instantaneous coordinate ($\Delta\varphi$). For practical reasons, the control system's main feedback is organized with a coefficient equal to one, ensuring clarity and ease of modeling.

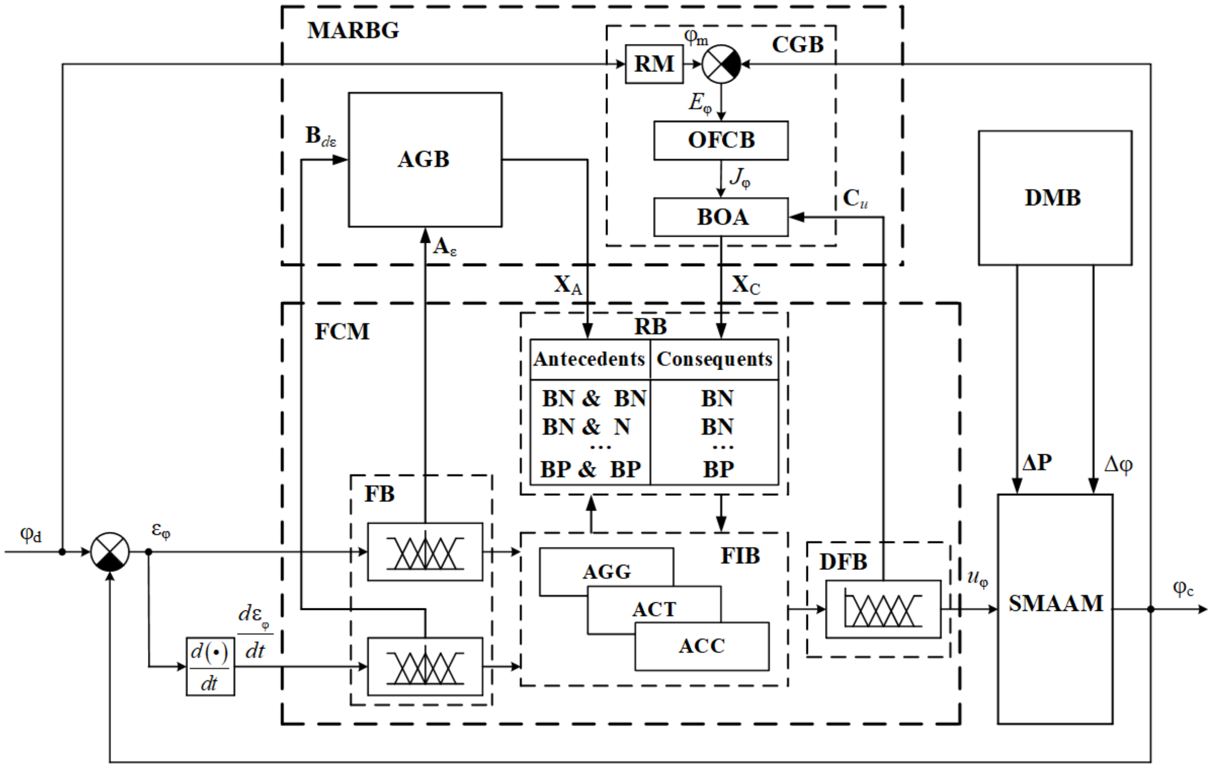

Fig. 1. Structure of the fuzzy control model with automated rule base generation for the artillery systems' actuators.

The FCM itself follows the classical Mamdani-type inference structure, encompassing all essential stages: fuzzification, aggregation, activation, accumulation, and defuzzification. Its rule base consists of conventional "If–Then" rules that connect antecedents with corresponding consequents. To automate the creation of this RB, a specialized mechanism for automated rule base generation is introduced, which is examined in detail below.

Mechanism of automated rule base generation utilizing a bioinspired optimization algorithm. The MARBG process unfolds in four distinct stages. The first stage is preliminary, where essential parameter adjustments and preparatory settings are carried out to ensure correct operation of the subsequent stages. The second stage focuses on generating rule antecedents, while the third stage addresses the generation of corresponding consequents, formulated as a discrete optimization task. Finally, the fourth stage, considered optional, is dedicated to fine-tuning the resulting model, allowing further enhancement of its quality indicators when required. This last step can be omitted if the system already demonstrates satisfactory performance.

Next, a detailed examination of each of the four stages is provided, with particular attention to their functional roles and interrelations within the overall mechanism.

Stage 1. Initial preparatory procedures. At the initial stage, a set of preparatory procedures must be carried out, without which the process of automated rule base generation cannot be initiated. First and foremost, it is necessary to define the linguistic terms for the two input variables ε_φ and $d\varepsilon_\varphi/dt$ of the fuzzy control model and for its output variable u_φ. Based on established methodological recommendations, the number of terms for input variables should generally range from three to seven, while for the output variable it is advisable to select between five and nine terms [18]. Once this choice has been made, the corresponding membership function forms are specified. The most commonly used and practically suitable options include Gaussian, triangular, or trapezoidal functions, depending on the desired trade-off between computational efficiency and approximation accuracy [19].

At the same stage, the selection of operators for the core inference procedures must be carried out. Typically, the "min" operator is employed for aggregation and activation, the "max" operator for accumulation, and the centroid method (center of gravity) for defuzzification, ensuring both transparency and interpretability of the inference process [19]. Additionally, normalizing coefficients are introduced (not shown in Fig. 1) in order to transform all input and output variables into relative units. For convenience, these coefficients are usually defined as the inverse of the maximum possible values of the corresponding variables [20]. Only after completing all these preliminary steps does it become possible to proceed to the subsequent stages, which involve the direct automated generation of the fuzzy rule base.

Stage 2. Generation of rule antecedents. The generation of rule antecedents is carried out in a fully automated manner by means of the AGB module, which operates on the previously defined vectors of linguistic terms $\mathbf{A}_{\varepsilon}$ and $\mathbf{B}_{d\varepsilon}$ for the input variables. At this stage, the structural framework of the rules as well as their antecedents vector $\mathbf{X}_{\mathrm{A}}$ are constructed by systematically generating all possible unique combinations of the selected terms, thereby ensuring complete coverage of the input space. As a result, the total number of rules is explicitly determined as the product of the number of linguistic terms associated with the first and second input variables. Once this exhaustive set of antecedents has been established, the process naturally advances to the subsequent stage, namely, the automated generation of appropriate consequents for each rule.

Stage 3. Generation of rule consequents. The automated generation of rule consequents is performed by the CGB module, which integrates a reference model, a comparison unit, an objective function evaluation block, and a bioinspired optimization algorithm. Within this framework, the entire set of consequents is represented as a vector $\mathbf{X}_{\mathrm{C}}$ of unknown parameters, thereby transforming the task into a discrete optimization problem. The dimensionality of this vector is equal to the total number of rules in the rule base, while each element of the vector is constrained to take values only from the set of linguistic terms $\mathbf{C}_{u}$ defined for the output variable.

For solving this optimization problem, the ant colony algorithm is proposed as an effective bioinspired method, all the details of which, as well as the features of application for rule base optimization are described in [17]. In this context, each iteration of the algorithm simulates the movement of artificial ants across a graph, where the nodes correspond to individual rules of the fuzzy rule base, and the edges represent the potential consequents associated with these rules. The search for the optimal solution is equivalent to identifying the shortest path in this graph, which corresponds to the most suitable vector of consequents yielding the minimal value of the objective function J_{φ}. During the iterative process, the algorithm consistently performs its key operations: traversal of nodes and edges by the ants, deposition of pheromone on the edges, as well as its evaporation and subsequent renewal, gradually decreasing the value of the objective function J_{φ}, ensuring convergence toward the optimal rule configuration. Before running the algorithm, it is also necessary to set the specific values of all its parameters as well as the desired value of the objective function $J_{\varphi\mathrm{d}}$, which serves as the benchmark to be approached throughout the optimization process [17].

In classical shortest-path problems addressed by the ant colony algorithm, the objective function is typically represented as the simple sum of traversed edges. In the present case, however, the situation is far more complex, as the optimization process is tightly coupled with the dynamic performance of the control system under investigation. The first critical step involves selecting an appropriate reference model against which the dynamic characteristics of the fuzzy-controlled system will be compared. Since, in the case of controlling the elevation (or rotational) angle of the gun barrel, the optimal transient response is characterized by an aperiodic nature (without overshoot or oscillations) and by the fastest possible settling time, it is appropriate to adopt transfer function (2) as the RM of the executive mechanism.

$$W_{\mathrm{RM}} = \frac{1}{\left(\tau_{\mathrm{RM}} s + 1\right)^{2}}, \tag{2}$$

where τ_{RM} is the desired time constant for the control process.

It is important to emphasize that, at this stage, by carefully selecting the type of reference model, tuning its parameters, and prescribing the desired value of the objective function, one can flexibly regulate the emulated proficiency level of the virtual operator. Consequently, depending on the intended scenario, whether high, medium, or low expertise, different forms of reference models, along with adjusted parameter values and objective function thresholds, can be employed to reproduce varying degrees of virtual control skill.

At the same time, specific considerations must be made for the modeling of the actuator itself. For instance, in the case of an electric drive, the generalized transfer function (3) can be employed as a representative model for carrying out the calculations.

$$W_{\text{ED}} = \frac{K_{\text{ED}}}{s\left(\tau_{\text{ED1}}s^2+\tau_{\text{ED2}}s+1\right)}, \tag{3}$$

where τ_{ED1} and τ_{ED2} are the drive time constants; K_{ED} is the drive gain.

To ensure the synthesis of a complete rule base capable of maintaining robust control performance under diverse conditions, it is essential to conduct simulations across a wide spectrum of operational scenarios. This includes transitions between different initial and final angular positions in both directions, exposure to various types of disturbances (step, impulse, and periodic), as well as systematic parameter variations across iterations. For example, with respect to the time constant τ_{ED1}, the DMB module modifies its value at the beginning of each simulation run in accordance with expression (4), thereby introducing variability into the process and ensuring that the resulting fuzzy control model retains its effectiveness under uncertain and dynamically changing conditions.

$$\tau_{\text{ED1}} = \tau_{\text{ED10}} + r_{\text{ED1}}(n)\delta_{\tau1}, r_{\text{ED1}}(n) = \text{rand}[-1,1], \tag{4}$$

where τ_{ED10} is the initial value of the time constant τ_{ED1}; r_{ED1} is the random number in the range from – 1 to 1 for the time constant τ_{ED1} at iteration n; $\delta_{\tau1}$ is the maximum deviation of the time constant τ_{ED1}.

Other parameters of the model should be changed in a similar manner.

With regard to the objective function J_φ, its evaluation at each iteration must be performed on the basis of the deviation E_φ between the models' outputs, computed in accordance with expression (5).

$$J_\varphi(\mathbf{X}_\text{C}) = \frac{1}{t_{\max}} \int_0^{t_{\max}} \left[\left(E_\varphi\right)^2 + k_1\left(\frac{dE_\varphi}{dt}\right)^2 + k_2\left(\frac{d^2E_\varphi}{dt^2}\right)^2 \right] dt, \tag{5}$$

where $t_{\max}$ is the total time of all simulations in different modes in one iteration; k_1 and k_2 are the weighting coefficients for the corresponding derivatives of E_φ.

Incorporating not only the deviation E_φ itself but also its first and second derivatives makes it possible to penalize oscillatory behavior in the transient process, thereby ensuring smoother and more stable system dynamics.

Once the optimization procedure converges to the best vector of consequents $\mathbf{X}_\text{C}$ and this solution is embedded into the fuzzy model, the construction of the rule base can be considered complete. At this point, the methodology advances to the final stage of the proposed approach.

Stage 4. Optional fine-tuning procedures. At the final stage, the optimization focuses on refining the parameters of the linguistic terms together with the adjustment of the normalizing coefficients, aiming to enhance the precision and overall efficiency of the control process. This procedure is applied selectively – only when the achieved quality indicators of the model require further improvement. If the system already exhibits stable and satisfactory performance, this step should be omitted.

Conversely, should the results remain inadequate even after completing all stages, including this one, it becomes necessary to return to the initial stage (Stage 1) in order to revise the fundamental settings, such as the number and configuration of linguistic terms, the choice of membership functions, or the selection of fuzzy inference operators.

Thus, the mechanism of automated rule base generation is formed, and the second of the key tasks of this study is solved. Proceeding further, we address the third key task, which involves carrying out a series of computational experiments aimed at substantiating the effectiveness and practical applicability of the proposed fuzzy control model.

5. Experiments

To evaluate the performance of the proposed fuzzy control model with automated rule base generation, a set of computational experiments was carried out in this study. The experiments were implemented on the basis of a simulation model of the gun barrel elevation electric drive, described by basic transfer function (6), which is suitable for using in game simulator environments.

$$W_{\mathrm{ED0}} = \frac{1.5}{s\left(0.21s^2 + 4.3s + 1\right)}. \tag{6}$$

In the course of simulation, both during the automated rule base generation and in subsequent verification experiments, the parameters of the considered transfer function were systematically varied according to the scheme analogous to formula (4). The maximum deviation δ for each parameter reached up to 50% of its nominal value. Additionally, the model incorporated the influence of coordinate disturbances of different types, thereby ensuring a more comprehensive assessment of the control system's robustness under diverse operating conditions.

In the course of synthesizing the fuzzy control model, the initial stage involved the definition of linguistic variables. Specifically, five terms (BN, SN, Z, SP, BP) were assigned to each input variable (ε_φ and $d\varepsilon_\varphi/dt$), while seven terms (VBN, BN, SN, Z, SP, BP, VBP) were chosen for the output variable u_φ. All linguistic terms were represented using triangular membership functions, whose vertices were arranged to guarantee an even partitioning of the full operational interval for all the variables. This configuration provides uniform coverage of the working domain, thereby ensuring consistency and accuracy in subsequent stages of fuzzy inference and rule base generation. Moreover, the "min" operator was employed for aggregation and activation, the "max" operator for accumulation, and the centroid method for defuzzification.

At the second stage of synthesis, the system automatically generated all possible unique pairwise combinations of the linguistic terms corresponding to the two input variables. As a result, a complete set of 25 distinct combinations was obtained, each of which served as the antecedent for one rule within the fuzzy knowledge base.

At the third stage, the consequents for each of the 25 previously generated rules were determined through the application of the ant colony optimization algorithm, configured with the following parameters: colony size – 25 ants; the number of elite ants – 15; pheromone deposition coefficient ρ = 0.5; weighting parameters α = 2, β = 1; pheromone quantity factor Q = 12. The optimization process was guided by the objective function defined in expression (5). To emulate the behavior of a highly skilled virtual opponent or ally, the desired value of the objective function was set to 10, while expression (2) with a time constant $\tau_{\mathrm{RM}} = 0.5$ s was adopted as the reference model. As a result of the optimization process, by the 73rd iteration an efficient rule base was obtained, for which the value of the objective function reached 8.064, i.e., below the predetermined threshold. The generated rule base, reflecting the most effective set of consequents for all formed rules, is presented in Table 1.

Table 1. Generated rule base of the fuzzy control model for the artillery system's actuator.

		Linguistic terms for the angle error ε_φ				
		BN	SN	Z	SP	BP
Linguistic terms for the derivative of the angle error $d\varepsilon_\varphi/dt$	BN	VBN	VBN	BN	BP	VBP
	SN	VBN	VBN	SN	BP	VBP
	Z	VBN	BN	Z	BP	VBP
	SP	VBN	BN	SP	VBP	VBP
	BP	VBN	BN	BP	VBP	VBP

Since at the third stage the achieved value of the objective function was already lower than the specified threshold, the fourth stage of refinement was not applied in this study. To confirm the efficiency of the developed fuzzy control model, a set of transient response graphs is presented, illustrating its operation under various conditions. For comparative analysis, a conventional PD controller was also employed, with its coefficients optimized through parametric tuning by the gradient method, using the same reference model and objective function as in the proposed approach. The obtained coefficient values of the PD controller were $K_{\mathrm{p}} = 2.13$ and $K_{\mathrm{d}} = 3.42$. However, unlike the fuzzy model, the classical controller demonstrated substantially inferior performance, achieving only a minimal objective function value of 54.56, which is several times higher than the threshold and the result of the proposed solution.

Fig. 2 presents the transient response curves corresponding to the processes of barrel elevation and depression, obtained under the conditions defined by the parameters of transfer function (6). In this experiment, the simulations were performed without the influence of coordinate disturbances, thereby allowing a clearer assessment of the intrinsic dynamic characteristics of the control system.

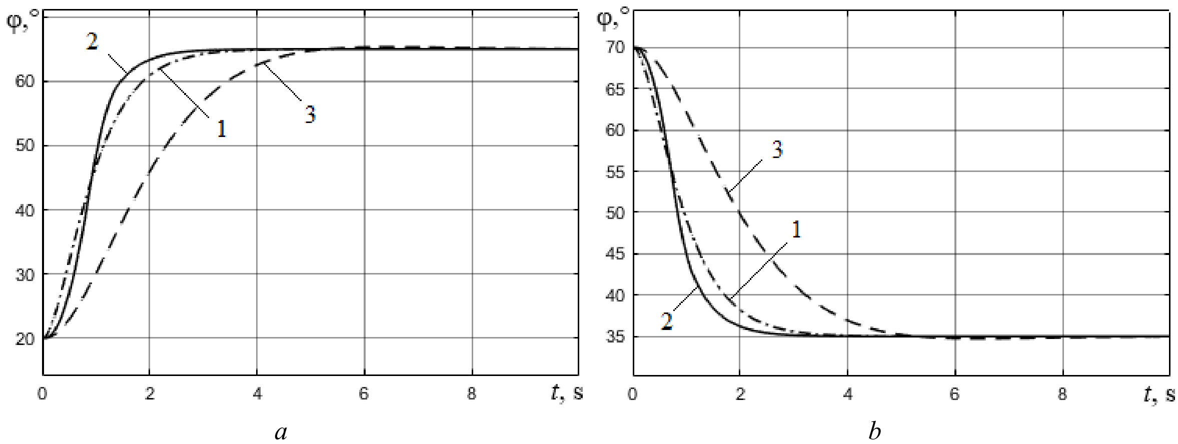

Fig. 2. Transient response curves corresponding to the processes of barrel (a) elevation from 20° to 65° and (b) depression from 70° to 35° for: 1 – RM; 2 – proposed FCM; 3 – PD controller.

Subsequently, Fig. 3 illustrates the transient responses of gun barrel elevation obtained using the model parameters defined by transfer function (6), this time under the influence of step-type coordinate disturbances. These results make it possible to evaluate the robustness of the proposed fuzzy control model in conditions where sudden external perturbations affect the dynamics of the actuator. In Fig. 3, the step disturbances began to act at a time of 5 s.

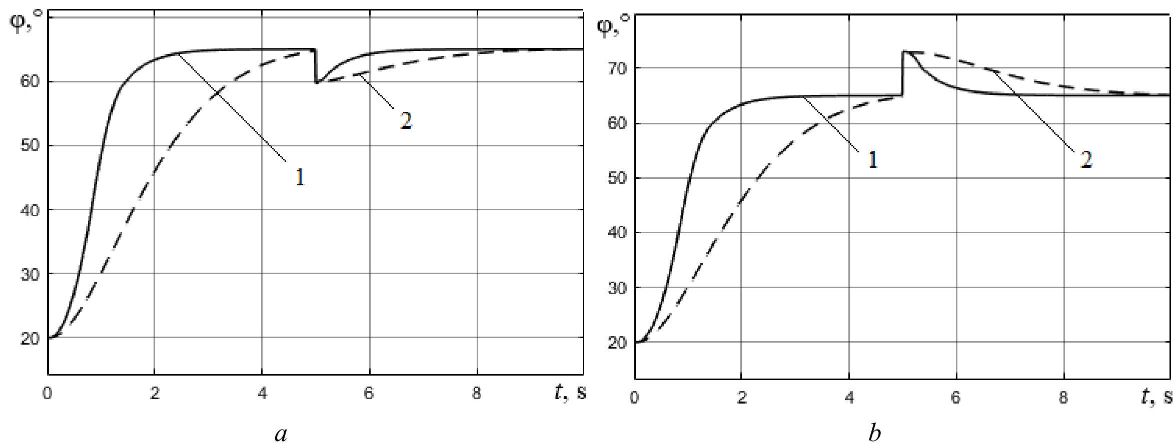

Fig. 3. Transient response curves at barrel elevation from 20° to 65° under the action of (a) positive step disturbance of +5° and (b) negative step disturbance of –8° for: 1 – proposed FCM; 2 – PD controller.

In turn, Fig. 4 presents the transient responses of the gun barrel elevation and lowering when time constants of the system model are increased by 50% and the gain is reduced by 50% relative to the nominal values defined in transfer function (6). This experiment demonstrates the adaptability of the proposed fuzzy control model to significant parametric variations, thereby confirming its effectiveness under conditions of pronounced model uncertainty.

Moreover, Fig. 5 presents the transient responses of the gun barrel elevation and lowering when time constants of the system model are reduced by 50% and the gain is increased by 50% relative to the nominal values of the transfer function (6). This experiment also demonstrates the adaptability of the proposed fuzzy control model to parametric disturbances.

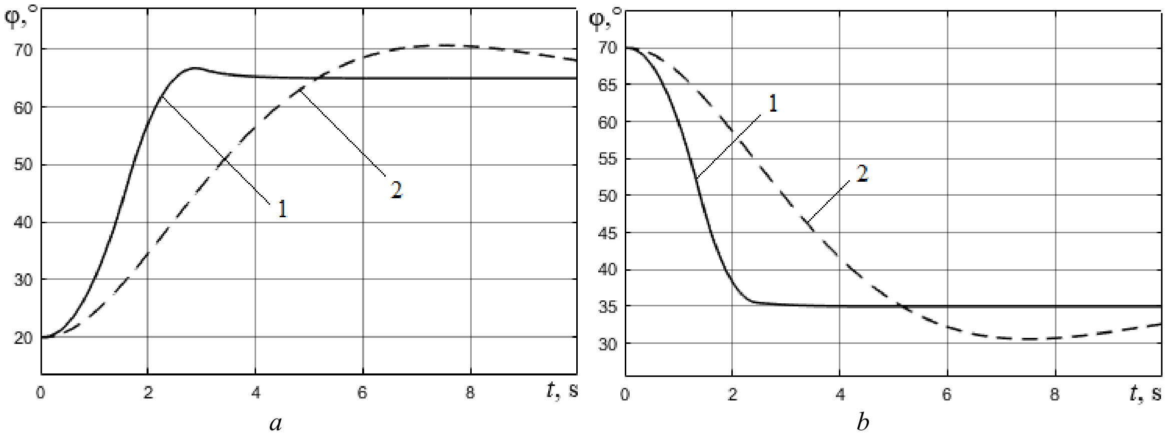

Fig. 4. Transient response curves at increasing time constants by 50% and reducing gain by 50% for the processes of barrel (a) elevation from 20° to 65° and (b) depression from 70° to 35° for: 1 – proposed FCM; 2 – PD controller.

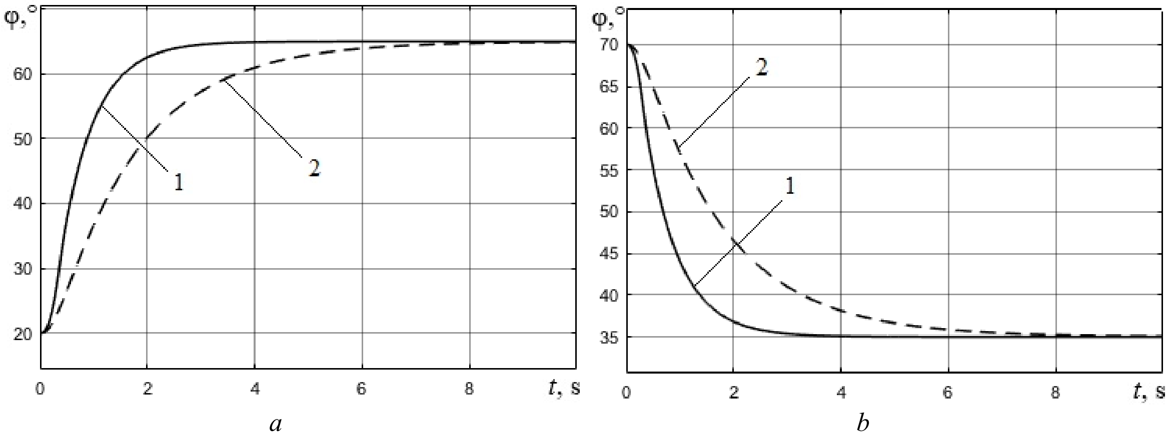

Fig. 5. Transient response curves at reducing time constants by 50% and increasing gain by 50% for the processes of barrel (a) elevation from 20° to 65° and (b) depression from 70° to 35° for: 1 – proposed FCM; 2 – PD controller.

Furthermore, in order to explicitly demonstrate the robustness characteristics of the synthesized fuzzy control model, Table 2 summarizes the outcomes of a series of computational experiments performed under variations of the actuator simulation model parameters. In particular, the table reports the response time t_r and overshoot σ values obtained for different parameter configurations, since these indicators represent the most essential criteria for evaluating the quality and reliability of the control process. For brevity, Table 2 provides only the results of simulations for upward barrel movement, as in the case of lowering, the quality indicators were consistently superior across all experimental conditions.

Table 2. Results of computational experiments performed under variations of the actuator simulation model parameters.

Experiment number	Parameters of the actuator simulation model			Quality indicators for FCM		Quality indicators for PD controller	
	τ_{ED1}, s	τ_{ED2}, s	K_{ED}	t_r, s	σ, %	t_r, s	σ, %
1	0.21	4.3	1.5	1.81	0	3.87	0.615
2	0.315	6.45	0.75	2.26	2.615	10.02	8.77
3	0.105	2.15	2.25	1.56	0	4.45	0
4	0.217	3.2	1	1.69	0	4.21	0.32
5	0.3	5.7	0.9	2.08	0	8.24	6.08

As follows from the data presented in Table 2, the fuzzy control model demonstrates a high degree of robustness to parameter variations of the actuator simulation model. Even under the most unfavorable conditions (when the time constants were increased by 50% and the transmission coefficient was reduced by half) the system response time increased by only 25%, with a minor overshoot of 2.615%. In all other scenarios, the performance degradation was negligible, and overshoot remained absent, confirming the stability and reliability of the proposed model. By contrast, the traditional PD controller exhibited substantially inferior performance: in the worst case, the response time nearly tripled and overshoot reached almost 9%, which poses a serious risk in practical artillery guidance scenarios. Moreover, the PD-based system handled step coordinate disturbances far less effectively (Fig. 3).

The obtained results convincingly demonstrate the high efficiency of the proposed fuzzy model in controlling the actuators of artillery mounts within game simulator environments. These findings validate the adequacy of the developed approach and its ability to ensure both stability and robustness under varying operating conditions. Consequently, the third and final research task is successfully solved.

6. Conclusion

In this study, a fuzzy control model with automated rule base generation for artillery system actuators in game simulators has been developed and comprehensively investigated. The proposed architecture incorporates a mechanism for automated rule base synthesis based on a bioinspired optimization approach, namely the ant colony algorithm, which enables the construction of highly efficient rule bases even in the absence of expert knowledge or under conditions where manual rule formulation is impractical or error-prone. This feature ensures adaptability and autonomy of the control system, making it particularly valuable in complex and uncertain environments.

The model demonstrates considerable potential for application in game simulators, where it can be employed to emulate the decision-making logic of virtual allies or adversaries, thereby enhancing the realism of simulated combat scenarios. By adjusting the parameters of the reference model and the objective function during the optimization process, it becomes possible to reproduce different levels of operator proficiency, ranging from novice to expert. This property also highlights the model's value as a training tool, as it allows operators to observe and analyze effective control strategies in diverse tactical situations. Unlike neural network–based player models, fuzzy models possess high degree of logical transparency, enabling direct study and analysis of their control strategies.

Experimental validation, carried out on the example of an electric drive simulation model responsible for artillery barrel elevation, confirmed the practical effectiveness of the approach. When benchmarked against a traditional PD controller, the proposed fuzzy model exhibited superior performance, maintaining robustness under random parameter variations of the drive model as well as under the influence of external disturbances. These results confirm the high efficiency, adaptability, and resilience of the developed model in comparison to conventional control solutions.

Finally, it should be emphasized that the scope of application of the presented model is not limited to electric drives. With appropriate adaptation of simulation models, the proposed fuzzy control model can be effectively extended to other types of artillery actuators, including hydraulic and electrohydraulic systems, thereby broadening its relevance and applicability to a wide range of technical and simulation environments.

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Модель нечіткого керування з автоматизованою генерацією бази правил для артилерійських систем в ігрових симуляторах

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Анотація

У даній статті представлено розробку та валідацію нечіткої моделі керування з автоматизованою генерацією бази правил для виконавчих механізмів артилерійських систем у ігрових симуляторах. Запропонована модель інтегрує біоінспірований механізм оптимізації на основі алгоритму мурашиної колонії, що дозволяє автоматично синтезувати ефективні бази правил без використання експертних знань. Такий підхід забезпечує адаптивність та автономність за невизначених умов, а також демонструє логічну прозорість, що дозволяє детально аналізувати стратегії керування. Модель може бути використана для симуляцій поведінки прийняття рішень віртуальними союзниками або противниками, представляючи їхні різні рівні кваліфікації шляхом коригування еталонних моделей та цільових функцій на стадії проєктування, що підвищує реалізм у моделюванні бойових сценаріїв. Експериментальні дослідження, проведені на прикладі імітаційної моделі електроприводу підйому ствола артилерійської установки, продемонстрували перевагу нечіткої моделі над традиційним ПД-контролером з точки зору робастності, ефективності та точності. Представлена методологія також може бути застосована для гідравлічних та інших типів виконавчих механізмів.

Ключові слова: ігрові симулятори; артилерійські системи; нечітка модель керування; генерація бази правил; модель виконавчих механізмів.