Complex Structural-Parametric Optimization of Fuzzy Control Systems Based on Bioinspired Algorithms

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Abstract
This article presents a comprehensive approach to the structural-parametric optimization of Mamdani-type fuzzy control systems (FCS) using a set of bioinspired methods. The proposed methodology integrates optimization of the number of linguistic terms (LT), rule base (RB) synthesis, selection of membership function (MF) types, parametric tuning, as well as the adjustment of fuzzy inference engine (FIE) operations and defuzzification methods in the most rational sequence. The approach is validated through its application to a FCS for an unmanned aerial vehicle (UAV). Experimental results demonstrate that the greatest improvements in control accuracy are achieved through the parametric optimization, with reductions in the objective function of up to 27.5%. The final optimization stage yielded only minor gains (5.6%), indicating its lower impact. The proposed optimization strategy enables the development of high-performance fuzzy systems with simplified implementations and reduced computational costs, making it suitable for embedded control applications in robotics and autonomous systems.

Keywords
Fuzzy control system, structural-parametric optimization, comprehensive approach, bio-inspired algorithms, unmanned aerial vehicle

1. Introduction

The design and development of complex technical systems across diverse domains of human activity, ranging from robotics and industrial automation to medicine and agriculture, are invariably associated with multifaceted optimization problems [1-3]. These challenges arise from the need to balance competing objectives, satisfy strict performance requirements, and ensure reliability, adaptability, and cost-efficiency under diverse operating conditions. As system complexity increases, so too does the dimensionality of the parameter space, often accompanied by strong nonlinearity, multimodality, and the presence of numerous local optima [4-7]. Moreover, structural decisions, such as the configuration of control architectures or system topologies, must often be made in tandem with parametric tuning, giving rise to highly interdependent structural-parametric optimization tasks. Conventional optimization

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techniques, though effective in narrowly constrained contexts, frequently fall short when addressing the intricate interrelations and uncertainties inherent in large-scale, real-world systems [8-10]. These limitations have catalyzed the exploration of more flexible, adaptive, and computationally intelligent approaches to system optimization.

One of the most promising directions in contemporary optimization research is the development of novel algorithms inspired by natural phenomena and biological systems [11-13]. Bioinspired optimization approaches have gained increasing attention due to their ability to efficiently explore complex and high-dimensional search spaces, often avoiding local optima and adapting well to non-linear and multi-objective formulations [14-17]. Among the most widely adopted and well-tested methods are genetic algorithms (GA) [18], particle swarm optimization (PSO) [19], ant colony optimization (ACO) [20], grey wolf optimization (GWO) [21], ant lion optimization (ALO) [22], whale optimization algorithm (WOA) [23], cuckoo search (CS) algorithm [24], Artificial Bee Colony (ABC) [25] etc. These techniques have been successfully applied to a wide range of engineering problems, including control system tuning, scheduling, structural design, power system planning, and robotics.

Moreover, recently, several newer bioinspired methods have emerged, aiming to improve convergence speed, adaptability, and robustness. These include the Tianji's horse racing optimization (THRO) [26], stellar oscillation optimizer (SOO) [27], goal programming-based algorithm for solving multi objective optimization problems [28], improved chicken swarm optimization with differential evolution (ICSODE) [29], animated oat optimization (AOO) [30], and enzyme action optimization (EAO) [31]. These approaches have shown significant promise across various domains, such as renewable energy systems, biomedical engineering, image processing, and machine learning model optimization. The continuous emergence of such algorithms highlights the relevance of nature-inspired computation in addressing complex real-world optimization challenges.

Fuzzy control systems, in turn, are increasingly adopted in domains requiring robust operation under uncertainty and imprecision [32, 33]. However, as systems grow in complexity and operate in dynamic environments, the design and tuning of fuzzy systems become increasingly challenging. The optimization of fuzzy systems includes multiple facets, ranging from the structural configuration of the rule base and membership function shapes, to parameter tuning and controller gain adjustment [34-36]. The inherent non-linearity and high dimensionality of fuzzy models often make conventional analytical or gradient-based optimization techniques insufficient. Therefore, a range of optimization strategies have been proposed, including multi-objective optimization, hybrid approaches, and adaptive tuning mechanisms, to refine fuzzy controller performance across varying application domains such as robotics, industrial process control, energy systems, and intelligent transportation [37-39].

In this context, bioinspired algorithms offer a particularly effective toolkit for the structural-parametric optimization of fuzzy systems [40-42]. Their global search capabilities, population-based nature, and flexibility make them suitable for simultaneously optimizing both discrete and continuous variables present in fuzzy system design. As demonstrated by numerous studies, methods such as ACO, GA, GWO, and other algorithms have been employed for optimizing membership function parameters, rule bases, and structural components [43-45]. These approaches enable the automated synthesis of fuzzy controllers that are well-tuned to specific system dynamics, thereby improving control accuracy, robustness, and adaptability in complex nonlinear systems.

Despite the substantial progress achieved in recent years, most existing studies primarily address isolated aspects of fuzzy system optimization, either focusing on parameter tuning or structural adjustment. However, the problem of holistic or complex optimization, which entails the systematic execution of all key synthesis procedures in a coherent and rational sequence using appropriate methods and technologies, remains largely unresolved. A fragmented optimization approach often limits the attainable performance and adaptability of fuzzy systems, particularly in complex, real-world applications.

Accordingly, the principal objective of this paper is to develop and validate a comprehensive approach to structural-parametric optimization, which integrates all critical stages of fuzzy system design within a unified, logically structured and the most rational sequence, which will allow to create fuzzy control systems for nonlinear dynamic objects with high quality indicators and robust properties with the shortest duration of the synthesis and implementation processes. The core contributions of this work are threefold: (1) a detailed analysis of the influence of each individual optimization procedure on the efficiency of the fuzzy system, as well as the necessary conditions for its direct execution; (2) the formulation of a stepwise approach to complex structural-parametric optimization, ensuring the most rational sequencing at integration of the core synthesis stages; and (3) a study of the effectiveness of the proposed approach using the example of a UAV's fuzzy control system.

2. Analysis of the influence and necessary conditions of individual optimization procedures execution on the efficiency of the FCS

In the design of real-world fuzzy systems under conditions of limited expert knowledge and absence of a priori information, complex structural-parametric optimization tasks may arise. Successful resolution of such tasks requires not only a suite of high-performance structural and parametric optimization methods but also their application in an appropriate sequence. An improper order of application can lead to suboptimal use of these methods, reducing their effectiveness and significantly increasing the overall computational cost of the design and optimization process. Therefore, determining an optimal sequence for structural-parametric optimization procedures based on the available methods and technologies is essential for enhancing the efficiency and success of FCS design.

To determine the optimal sequence of structural-parametric optimization procedures in the development of Mamdani-type FCSs, it is advisable to analyze the impact of each individual procedure on the overall effectiveness of the system, as well as the necessary conditions for its direct implementation. The main procedures involved in the structural-parametric optimization of Mamdani-type FCSs typically include: (1) optimization of the rule base; (2) optimization of the number of linguistic terms for input and output variables; (3) optimization of the membership function types for linguistic terms; (4) optimization of the FCS parameters; and (5) optimization of the types of core operations in the fuzzy inference engine (aggregation, activation, accumulation), as well as the defuzzification method.

The rule base optimization procedure involves determining the optimal consequents vector and the optimal number of rules (i.e., rule base reduction in terms of rules count or rules components). This procedure is effectively implemented using the multi-agent method based on ACO developed in [43]. As such, rule base optimization is often a primary task in the structural-parametric optimization of a fuzzy system. This is because evaluation of the fuzzy system's effectiveness and calculation of its objective function during optimization of MF types and parameters, FIE procedures, and the defuzzification method requires a pre-constructed RB with a predefined optimal consequents vector. The only exception is the optimization of the number of LTs for input and output variables. The structural optimization method for FCSs proposed in [46], which allows efficient optimization of both the number of linguistic terms and the rule base itself for each LTs configuration.

The procedure for optimizing the types of fuzzy membership functions enables the selection of the most suitable membership function for each linguistic term of all input and output variables in a FCS. This optimization aims to enhance system accuracy and performance while also reducing the complexity of subsequent parametric optimization by minimizing the total number of tunable parameters. The procedure can be effectively implemented using the method proposed in [44], which employs a combination of bioinspired evolutionary global optimization algorithms to search for optimal LTMFs.

Parametric optimization of Mamdani-type FCSs involves the tuning of adjustable parameters of LTMFs as well as normalization coefficients associated with input and output variables. This process is essential for enhancing system accuracy and improving the effectiveness of solving specific tasks. Since setting specific LTMFs parameter values is only feasible after their types have been determined, the LTMFs parametric optimization must follow their types optimization. Otherwise, any later change in LTMFs types would require re-performing the parameter optimization procedure, resulting in unnecessary computational overhead. In turn, the procedures for optimizing fuzzy system parameters, namely the parameters of LTMFs and normalization coefficients, can be effectively implemented using hybrid multi-agent methods, such as the hybrid improved GWO developed and investigated in [45]. However, if a sufficiently high level of accuracy and performance has already been achieved during the preceding optimization stages, parametric optimization of LTMFs and normalization coefficients may be carried out using individual local search methods. These include, in particular, the gradient descent method or the extended Kalman filter algorithm (EKF) [41, 47].

The optimization procedures for selecting the types of core operations in the fuzzy inference engine (aggregation, activation, and accumulation) as well as the defuzzification method, can be applied to improve the accuracy of a FCS and enhance its effectiveness in solving the target tasks. However, the implementation of these procedures is advisable only after the prior synthesis and optimization of the fuzzy system's RB, and thus after the optimization of the number of LTs, which must precede the RB optimization. In the process of optimizing the fuzzy inference operations, the following core operators can be considered: for aggregation – "min" or "prod"; for activation – "min", "prod", or "average"; for accumulation – "max", "sum", bounded or drastic union, and the λ-sum operation [48]. For defuzzification, the available methods include the centroid (center of gravity), bisector, right maximum, left maximum, and middle of maximum techniques [48]. Given the relatively small number of alternative types for FIE operations, their optimization can be formulated as a single discrete optimization problem with a limited set of alternatives. This problem may be solved using full enumeration of all possible combinations, stochastic search (random generation of FIE operation combinations to identify the best option), or a sequential search method. The latter approach, proposed in [46], has been successfully applied to optimize the number of linguistic terms and the system's RB.

Considering the above-mentioned requirements for the rational sequence of structural-parametric optimization procedures in Mamdani-type fuzzy systems, Table 1 outlines, for each optimization procedure, all the prerequisite procedures that must precede it. Based on the analysis of the requirements presented in Table 1 and the aforementioned considerations, a step-by-step approach to comprehensive structural-parametric optimization of Mamdani-type FCS can be formulated.

Table 1
Requirements for the sequence of structural-parametric optimization of fuzzy systems of Mamdani type

Optimization procedure of fuzzy control system	Procedures that must precede
Rule base	Number of LTs for input and output variables
Number of LTs for input and output variables	-
Types of LTMFs	Rule base, number of LTs for input and output variables
Parameters of LTMFs and normalization coefficients	Rule base, number of LTs for input and output variables, types of LTMFs
Types of FIE operations (aggregation, activation, and accumulation) and defuzzification method	Rule base, number of LTs for input and output variables

3. Approach to complex structural-parametric optimization of Mamdani-type fuzzy control systems

The developed structural-parametric optimization approach is presented as a block diagram in Figure 1. In the proposed approach to comprehensive structural-parametric optimization of Mamdani-type fuzzy systems (Figure 1), the initial procedures involve the optimization of the number of linguistic terms and the synthesis and optimization of the rule base. These procedures are executed concurrently using the structural optimization method described in [46]. According to this method, the optimal number of LTs is determined through sequential or stochastic search, coupled with the simultaneous synthesis and optimization of the corresponding rule base for each generated variant. The RB is synthesized with an optimal consequent vector and an optimal number of rules using a multi-agent method based on the ACO.

Upon completion of these procedures, a verification step is conducted to determine whether the design objectives of the fuzzy system, such as the required accuracy and other performance indicators, have been achieved. If the verification yields a positive result, the process of structural-parametric optimization is considered complete, and the developed and optimized FCS may be implemented using appropriate hardware-software platforms and subsequently applied to solve the targeted tasks. Otherwise, the process proceeds to the next optimization stages according to the proposed approach (Figure 1). As outlined in the approach, the subsequent procedures are performed sequentially: optimization of the LTMFs types, system parameters, fuzzy inference engine operations, and the defuzzification method.

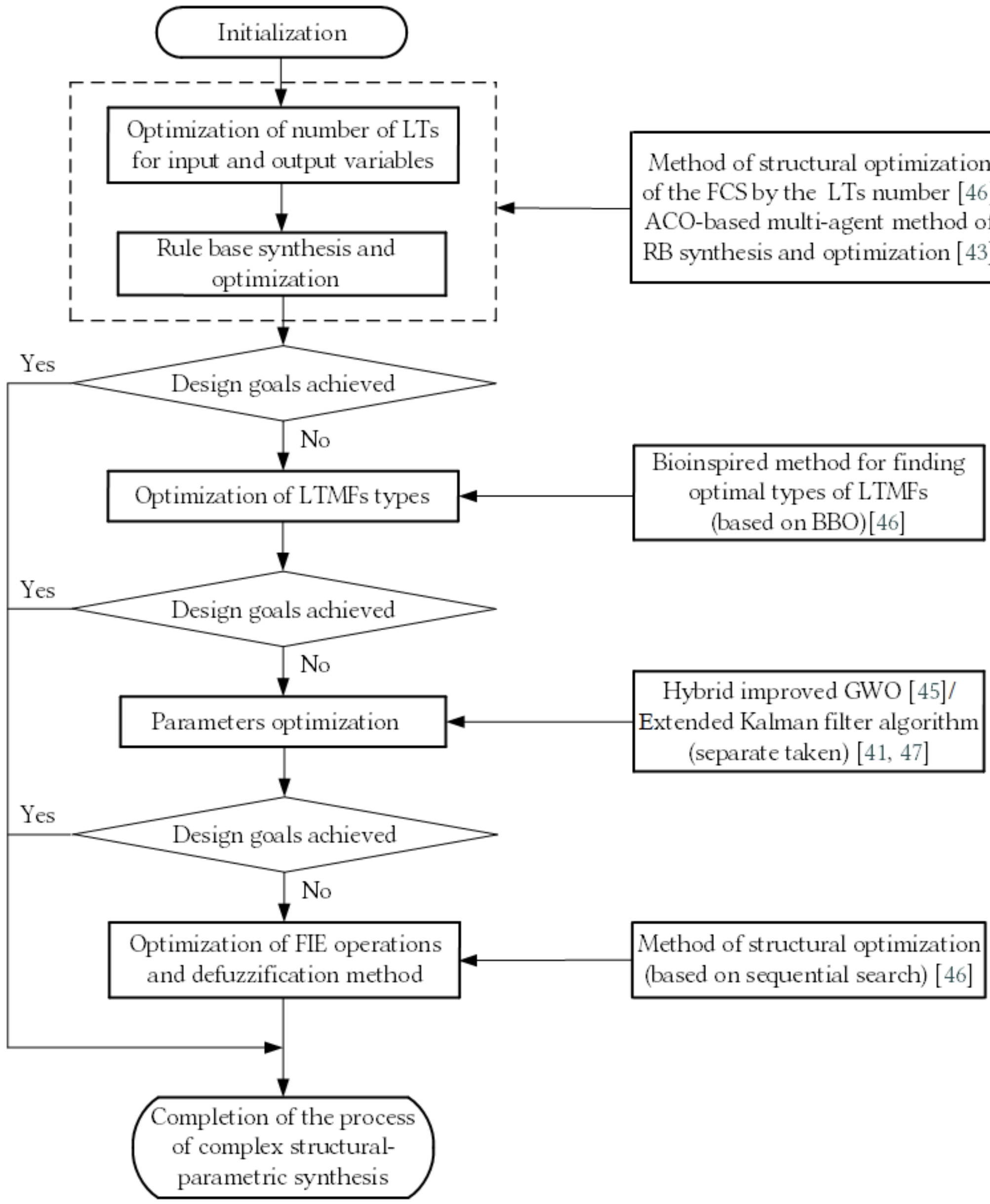

Figure 1: Block diagram of the approach to complex structural-parametric optimization of the Mamdani type FCS.

The optimization of LTMFs types is carried out using a bioinspired method developed in [44], based on genetic algorithms, artificial immune systems (AIS), or biogeography-based optimization. Parameter optimization of the fuzzy system can be conducted using the improved hybrid grey wolf optimization method proposed in [45], or via local search techniques such as the extended Kalman filter algorithm [41, 47]. The optimization of fuzzy inference operations and the defuzzification method is most appropriately performed using exhaustive search, stochastic search, or the sequential search method [46].

After the execution of each of these procedures, a verification step is performed to assess whether the system has achieved the desired performance objectives. If the required level of effectiveness is reached, subsequent optimization steps may be skipped to avoid unnecessary computational overhead.

The developed approach to the comprehensive structural-parametric optimization of Mamdani-type fuzzy systems (Figure 1) can also be applied to the optimization of Takagi–Sugeno fuzzy systems. In this case, instead of optimizing the rule base using ACO-based methods, the optimization of the rule consequent weight coefficients is performed using the improved hybrid GWO method proposed in [45].

To validate the effectiveness and rationality of the proposed approach, this study performs a comprehensive structural-parametric optimization of a Mamdani-type fuzzy system for UAV flight control. In turn, this study does not present a comparison of the employed bioinspired methods with their counterparts in terms of efficiency, time, and computational costs during the optimization procedures, as such comparisons have already been conducted extensively in previous research, including benchmarks against classical optimization methods.

4. Study of the effectiveness of the proposed approach using the example of a UAV's fuzzy control system

The structural-parametric optimization procedures were carried out in accordance with the proposed approach for the altitude automatic control system of the UAV, whose detailed description, mathematical model, and key technical specifications are provided in [46]. The studied Mamdani-type fuzzy altitude controller implements the control law defined by equation (1), while the UAV's mathematical model consists of a system of equations presented in [46].

$$u = f_{\mathrm{FC}}\left(K_{\mathrm{P}}\varepsilon_z, K_{\mathrm{D}}\dot{\varepsilon}_z, K_{\mathrm{I}}\int \varepsilon_z dt\right), \tag{1}$$

where u is the actual control signal; ε_z is the altitude control error; K_{P}, K_{D}, and K_{I} are the normalization coefficients of the controller.

The comprehensive structural-parametric optimization procedures of the described FCS were conducted for the case of UAV flight at a fixed altitude over mountainous terrain with complex topography, which is thoroughly examined in [46]. The primary design objective was to achieve the highest possible altitude control accuracy (i.e., the lowest possible value of the objective function J_1, defined by equation (2)) for the FCS under a fixed number of iterations during the optimization procedures.

$$J_1(x, v_x, \mathbf{S}) = \frac{1}{x_{\max}} \int_0^{x_{\max}} \left[\left(z_{\mathrm{D}}(x) - z_{\mathrm{R}}(x, v_x, \mathbf{S})\right)^2\right] dx, \tag{2}$$

where x is the horizontal coordinate; $x_{\max}$ is the length of the terrain section for which the calculations were made; v_x is the flight speed along the coordinate x; S is the vector of optimized parameters or components of the structure for each specific optimization procedure of the approach; z_{D} is the specified value of the flight altitude over mountainous terrain; z_{D} is the real value of the flight altitude.

Thus, for the purpose of detailed analysis, no fixed target value of the objective function (2) was predefined at the beginning of the fuzzy system design, and no verification of goal achievement was performed after each optimization procedure during the process. All major optimization procedures of the proposed approach (Figure 1) were executed sequentially, with a specified number of iterations allocated to each procedure.

Since the first two procedures, namely, the optimization of the number of linguistic terms and the synthesis and optimization of the RB, were successfully carried out for the given UAV altitude control system in [46], they were not repeated in the present study. Instead, the best results obtained in [46] using the structural optimization method based on selecting the optimal number of linguistic terms were taken as the starting point for the subsequent optimization procedures. Specifically, the optimal vector of linguistic term numbers and the corresponding synthesized RB with 36 rules and an optimal consequent vector were adopted, for which the achieved value of the objective function (2) at this stage was $J_1 = 0.119$. In turn, these results in paper [46] were obtained in 8 iterations.

Following this, in accordance with the proposed approach (Figure 1), the third procedure — optimization of the types of LTMFs — was carried out to further enhance the accuracy of altitude control. This procedure was performed using a bioinspired method for selecting optimal membership functions based on evolutionary algorithms, as developed in [44]. At the initial stage of LTMFs type optimization, the set of alternative MFs included all major types of functions described in [44]. The parameters of these MFs were chosen to ensure a uniform distribution of linguistic terms across the operational ranges of all three input variables and the output variable of the fuzzy altitude control system. Initially, triangular membership functions were assigned to all linguistic terms of the controller. Under this configuration, the total number of tunable parameters required to implement all terms of the UAV's fuzzy altitude controller was preliminarily set at 54.

As a composite objective function J_C for executing the LTMFs type optimization, expression (3) was selected [44].

$$J_C = J_1 + k_{J2} J_2, \tag{3}$$

where J_2 is the objective function that determines the complexity of further parametric optimization of a fuzzy system; k_{J2} is the weighting factor.

In turn, the component of the objective function J_1 was calculated according to expression (2), while J_2, which evaluates the complexity of subsequent parameter optimization, was computed as the total number of adjustable parameters of the LTMFs set based on expression (4) [44].

$$J_2 = \sum_{i=1}^{n} \sum_{q=1}^{\tau_i} k_{in}^{i}(q) + \sum_{j=1}^{m} \sum_{k=1}^{\tau_j} k_{out}^{j}(k), \tag{4}$$

where $k_{in}^{i}(q)$ and $k_{out}^{j}(k)$ are the numbers of optimized parameters of the q-th linguistic term for the i-th input variable and the k-th term for the j-th output variable depending on their membership functions type; n and m are the total numbers of input and output variables; τ_i and τ_j are the total numbers of LTs for the i-th input variable and j-th output variables.

The weighting coefficient for J_2 was set $k_{J2} = 0.002$. Prior to the execution of the LTMFs optimization procedure for the fuzzy altitude controller with triangular MFs, the initial values of the objective functions were as follows: $J_C = 0.227$, $J_1 = 0.119$, and $J_2 = 54$.

Since the previous optimization procedures (i.e., optimization of the number of LTs and rule base) had already enabled the fuzzy altitude control system for the UAV to achieve sufficiently high control accuracy (J_1 = 0.119), the iterative search for the optimal vector of membership functions was conducted using only a single global optimization evolutionary algorithm, namely, the biogeography-based optimization algorithm. This choice was made to reduce computational and time costs, as BBO demonstrated the best performance for membership functions types optimization in the studies reported in [44].

During the execution of the LTMFS type optimization using the BBO algorithm, its core parameters were experimentally tuned for this specific task. In particular, an ecosystem was initialized with Z_{max} = 100 habitats (islands). The species migration rates as functions of the number of species per island, $\lambda(N_S)$ and $\nu(N_S)$, were assumed to be linear, with maximum values $\lambda_{max} = \nu_{max} = 1$. The mutation operator coefficient was set to r = 0.1, and the maximum allowable number of species per island (corresponding to the optimal habitat suitability index f_{opt}) was set at N_{Smax} = 10. The habitat suitability index f was calculated as the inverse of the composite objective function J_C. The stopping criterion for the optimization process was defined as reaching the maximum number of iterations N_{max} = 100.

Upon completion of the LTMFs type optimization using the BBO algorithm for the FCS, the composite objective function J_C was successfully reduced to 0.184 (an 18.9% decrease), the performance objective J_1 was lowered to 0.098 (a 17.6% improvement), and the complexity criterion J_2 decreased to 43 (a reduction of 11 parameters). These results indicate that the optimization procedure was effectively carried out in accordance with the proposed comprehensive algorithm. As a result, both the altitude control accuracy and the overall simplicity of the LTMFs structure were improved, significantly facilitating the subsequent parametric optimization of the designed fuzzy control system.

In turn, the optimal membership function vector S obtained using the BBO algorithm has the form:

$$\begin{gathered}\mathbf{S} = \{Gs1FN, TrpFN, TrFN, Gs1FN, SgFN, ZFN, Gs1FN, SFN, \\ Gs1FN, Gs1FN, TrFN, ZFN, GbFN, Gs1FN, TrFN, TrFN, Gs1FN, SFN\},\end{gathered} \tag{5}$$

where *Gs*1*FN*, *TrpFN*, *TrFN*, *SgFN*, *ZFN*, *SFN*, and *GbFN* are the Gaussian 1st type, trapezoidal, triangular, sigmoid, Z-shaped, S-shaped, and bell-shaped functions.

Subsequently, in accordance with the approach presented in Figure 1, the accuracy and efficiency of the UAV altitude control system were further improved by performing the next procedure, namely, the parametric optimization. Since the preceding optimization of the number of LTs, the RB, and the types of LTMFs had already yielded sufficiently high accuracy and performance for the developed system (J_1 = 0.098), only the tunable parameters of the membership functions were optimized in this stage. To significantly reduce computational costs, this procedure was carried out using a single local search algorithm, specifically the Extended Kalman Filter algorithm. In the application of the EKF algorithm, the initial values of the a posteriori error covariance matrix were selected as $P_0 = 40900 I_{43}$, where I_{43} is the identity matrix of size 43. The process noise covariance matrix was set to $Q = 3900 \cdot I_{43}$. The measurement noise covariance matrix R was considered scalar in this case, with R = 500, as the fuzzy altitude controller has only one output (the control signal u). The stopping criterion for the optimization process was defined as the maximum number of iterations N_{max} = 100. The objective function for this stage of optimization was J_1, computed according to (2).

The performed parametric optimization of the LTMFs resulted in a significant improvement in the accuracy of UAV flight control. Specifically, the value of the objective function J_1 was reduced to 0.071 (a 27.5% decrease), which confirms the effectiveness and appropriateness of applying the EKF algorithm for this procedure. The resulting form of the controller's LTMFs with the optimized parameters is presented in Figure 2.

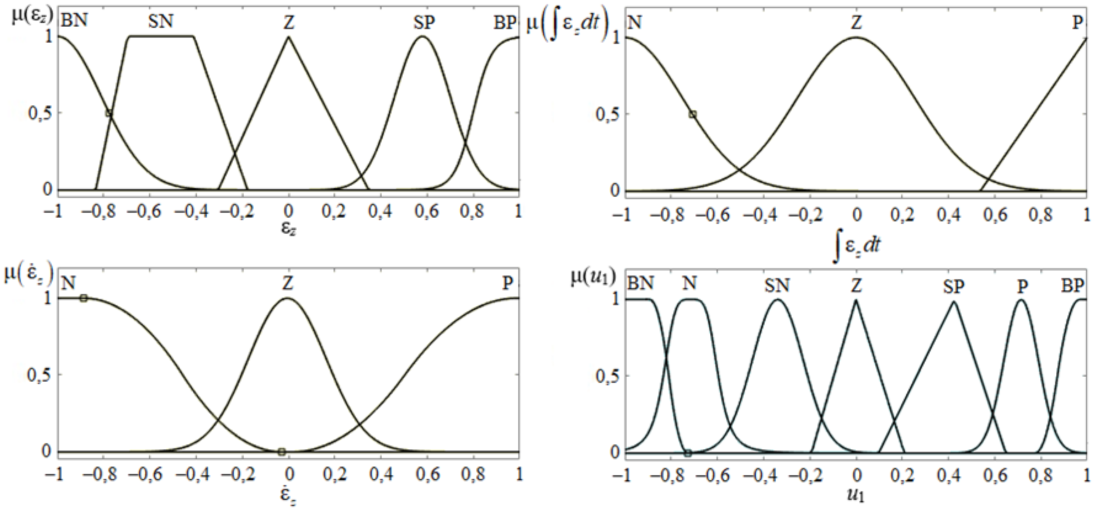

Figure 2: LTMFs with the optimized types and parameters for the UAV's control system.

The final optimization procedure within the proposed approach involves the optimization of the types of FIE operations and the defuzzification method. This procedure was carried out after the parametric optimization of the LTMFs to further improve the accuracy of UAV altitude control, using a sequential search method proposed in [46], which has previously proven effective in optimizing the number of linguistic terms and the rule base. During this stage, all major types of FIE operations and defuzzification methods were iteratively evaluated through sequential substitution, with the corresponding objective function (2) computed for each configuration to identify the best-performing option. The optimization process began with the aggregation operation and proceeded through the activation and accumulation operations, concluding with the defuzzification method. To enhance the effectiveness of this approach, the sequential search was conducted over two full cycles. Initially, the following configuration was used: the aggregation operation was set to "min", the activation to "min", the accumulation to "max", and the defuzzification method to the center of gravity. During the procedure, 12 iterations were performed per cycle, resulting in a total of 24 iterations over two cycles.

As a result of the optimization, the following configuration was identified as optimal: aggregation – "min", activation – "prod", accumulation – "max", and defuzzification – center of gravity. As seen from the results, only the activation operation changed (from "min" to "prod"), while the remaining FIE operations and the defuzzification method remained unchanged. This modification led to a further reduction in the value of the objective function from 0.071 to 0.067 (a 5.6% improvement), thereby slightly increasing the accuracy of the UAV's altitude control. Conversely, changes to other types of FIE operations and defuzzification methods only resulted in an increase in the objective function value.

Table 2 presents the overall results of the comprehensive structural-parametric optimization procedures for the UAV's fuzzy altitude control system, implemented using the proposed approach, where *N* denotes the number of iterations for each corresponding procedure.

Table 2
Results of the comprehensive structural-parametric optimization procedures for the UAV's fuzzy altitude control system

Optimization procedure	N	J_1	Optimization result
Optimization of the LTs number and the RB synthesis	8	0,119	Achieved J_1 = 0.119; number of RB rules decreased from 61 to 36
Optimization of LTMF types	100	0,098	J_1 decreased by 17.6%; number of LTMF parameters decreased from 54 to 43
LTMF parametric optimization	100	0,071	J_1 decreased by 27.5%
Optimization of FIE operations and the defuzzification method method	24	0,067	J_1 decreased by 5.6%

As a result of the optimization process, the objective function value (2) was reduced to J_1 = 0.067 through the execution of 8 iterations in the first two procedures (optimization of the LTs number and the rule base), 100 iterations in the third procedure (optimization of LTMF types), 100 iterations in the fourth procedure (parametric optimization), and 24 iterations in the final procedure (optimization of FIE operations and the defuzzification method).

As shown in Table 2, the UAV flight control system optimized using the proposed integrated approach demonstrates significantly higher control accuracy and improved performance compared to the system with only the number of LTs and the RB optimized, as described in [46]. This confirms the high effectiveness of the proposed approach to the comprehensive structural-parametric optimization and supports the feasibility and utility of the primary procedures involved. Moreover, this comprehensive approach has also demonstrated high effectiveness during its application to the development of FCSs for other complex technical objects, such as a pyrolysis plant and an electric vehicle — an outcome that is planned to be presented in future studies.

5. Conclusions

This study proposes an advanced approach to comprehensive structural-parametric optimization of fuzzy control systems. The main novelty of the developed approach is that it combines all critical stages of fuzzy system design within a unified, logically structured and the most rational sequence, which makes it possible to create fuzzy control systems for nonlinear dynamic objects with high quality indicators, robust properties and simplified software and hardware implementation while maintaining shortest duration of the synthesis process and minimal computational costs. This approach includes the optimization of the number of linguistic terms for input and output variables, synthesis and optimization of the rule base, selection of optimal types of membership functions, parametric optimization, as well as the identification of optimal fuzzy inference engine operations and defuzzification method. Moreover, the core optimization procedures of this approach are performed using a specially selected set of highly efficient and well-established bioinspired algorithms that have repeatedly proven their superiority in a number of previous studies.

The effectiveness of the proposed approach has been validated through its application to the comprehensive structural-parametric optimization of a fuzzy altitude control system for the UAV. Analysis of the experimental results indicates that the first two optimization procedures (LTs number and RB optimization) are foundational within the proposed methodology. They allow for the identification and implementation of highly flexible and effective fuzzy control and decision-making strategies by forming optimized rule bases in number and consequents. As a result, this ensures high efficiency, interpretability, and logical transparency of the fuzzy systems while preserving implementation simplicity. Subsequently, the optimization of LTMF types significantly improves the accuracy and performance of the FCS following the foundational procedures. It also simplifies the next phase (parametric optimization) by reducing the number of LTMF parameters subject to optimization. Parametric optimization, in turn, provides the most substantial improvement in system performance at the penultimate stage of design, requiring relatively low computational effort, which makes it one of the most important stages of comprehensive optimization. For instance, this procedure reduced the objective function J_1 for the UAV's control system by 27.5%. The final optimization stage, involving the tuning of FIE operations and the defuzzification method, was found to have the least impact on overall system performance. In the case of UAV's FCS, it resulted in only a 5.6% improvement in performance. Therefore, this procedure can be omitted in a number of cases, which will further reduce the computational and time costs of the entire design and optimization process.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT in order to improve writing style and Grammar. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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