

A HYBRID COMBINATIONAL APPROACH TO SENSITIVITY QUANTIFICATION IN MEMBERSHIP FUNCTION SELECTION DURING FUZZIFICATION OF SERVER PARAMETERS

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In the process of efficiently managing request flows within information systems, accounting for the individual characteristics of servers plays a crucial role. Traditional load balancing algorithms—such as Round Robin, Weighted Round Robin, and regional distribution methods—typically allocate requests in a cyclic manner or based solely on predefined weight coefficients. These approaches fail to consider real-time server load levels, response speed, or operational state. This paper proposes a novel fuzzy logic-based model for request flow management, with particular attention given to the selection of appropriate membership functions for the linguistic representation of server parameters. During the fuzzification phase, the sensitivity of membership functions is quantified and optimized through a combinational hybrid approach. Experimental results demonstrate that the proper selection of membership functions enhances the accuracy of decision-making and reduces the degree of uncertainty. Consequently, the proposed approach significantly improves the flexibility, precision, and stability of request flow management in distributed server environments.

Key words: fuzzification, membership functions, sensitivity quantification, combinational hybrid approach, server load balancing, fuzzy logic, system reliability, adaptive control, linguistic modeling, request flow optimization, normalized sensitivity index, system.

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ГИБРИДНЫЙ КОМБИНАЦИОННЫЙ ПОДХОД К КОЛИЧЕСТВЕННОЙ ОЦЕНКЕ ЧУВСТВИТЕЛЬНОСТИ ПРИ ВЫБОРЕ ФУНКЦИИ ПРИНАДЛЕЖНОСТИ В ПРОЦЕССЕ ФАЗЗИФИКАЦИИ ПАРАМЕТРОВ СЕРВЕРА

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В процессе эффективного управления потоками запросов в информационных системах учет индивидуальных характеристик серверов играет решающую роль. Традиционные алгоритмы балансировки нагрузки, такие как Round Robin, Weighted Round Robin, и методы регионального распределения обычно распределяют запросы циклически или на основе только предопределенных весовых коэффициентов. Эти подходы не учитывают уровни нагрузки серверов в реальном времени, скорость ответа или рабочее состояние. В данной статье предлагается новая модель управления потоками запросов на основе нечеткой логики, с особым вниманием к выбору соответствующих функций принадлежности для лингвистического представления параметров серверов. На этапе фаззификации чувствительность функций принадлежности количественно оценивается и оптимизируется с помощью комбинированного гибридного подхода. Экспериментальные результаты показывают, что правильный выбор функций принадлежности повышает точность принятия решений и снижает степень неопределенности. Следовательно, предложенный подход значительно повышает гибкость, точность и стабильность управления потоками запросов в распределенных серверных средах.

Ключевые слова: фаззификация, функции принадлежности, количественная оценка чувствительности, комбинированный гибридный подход, балансировка нагрузки серверов, нечеткая логика, надежность системы, адаптивное управление, лингвистическое моделирование, оптимизация потока запросов, нормализованный индекс чувствительности, система.

Introduction. In modern information and communication systems, the rapid increase in the number of users, the growing complexity of computational processes, and the operation of services in real-time mode have led to a significant rise in the volume of requests directed to servers. Under the constraints of limited computational resources, this situation has made it increasingly challenging to ensure continuous system operation, maintain response speed, and preserve the quality of service. Consequently, the issue of achieving effective load balancing has become a critical problem in contemporary distributed computing environments [1–3].

According to statistical data, the volume of global Internet traffic is projected to reach 175 zettabytes per year by 2025 [4]. At the same time, Gartner analytics reports indicate that poorly balanced server infrastructures cause companies to experience an average annual economic loss of approximately 2.5 million USD [5–7].

In most cases, information systems deliver services through multiple servers or computing nodes. In such environments, the problem of uneven resource utilization arises, where

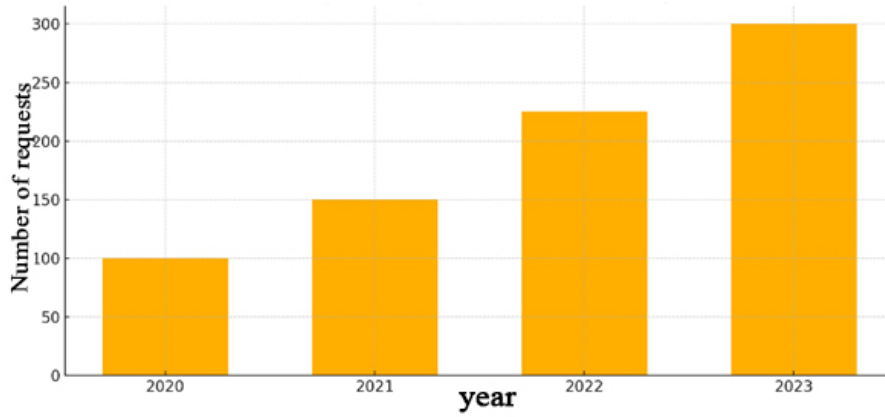


Fig. 1. Growth dynamics of online request volumes during the period 2020–2023

certain servers become overloaded while others remain underutilized. Since servers differ in computational power, memory capacity, and network latency, achieving optimal load distribution becomes a complex combinatorial problem [8]. This challenge becomes even more pronounced in systems based on microservice architectures, where significant variations in request flow direction, intensity, and priority are observed. As a result, dynamic load balancing strategies are required to ensure efficient and stable system performance [9–11].

According to Forrester Research analytics, between 2020 and 2023, the average number of user requests recorded by online stores increased by more than 300 % [12]. This trend underscores the growing necessity of implementing effective load balancing mechanisms that ensure the continuous, stable, and well-balanced operation of not only network infrastructures but also server resources (Fig. 1). Consequently, in the process of optimizing server request flows, researchers have increasingly moved beyond traditional deterministic approaches, adopting artificial intelligence-based methods, particularly fuzzy logic models, which enable the assessment of uncertainty and enhance flexibility in decision-making.

In information systems, the volume of load directed to servers continuously fluctuates over time. This variability is referred to as the dynamic load imbalance problem, which directly affects the overall system performance, including request processing speed, latency level, and the efficiency of resource utilization [13]. One of the key indicators for evaluating system performance is the degree of load distribution among servers. This indicator is typically measured using variance, which reflects the extent to which individual server loads deviate from the average load value.

The variance of load imbalance is expressed by the following formula:

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (L_i - \mu)^2, \quad (1)$$

where σ^2 — the variance of load imbalance in the system; L_i — the current load value of the i -th server; μ — the average load across all servers, defined as:

$$\mu = \frac{1}{N} \sum_{i=1}^N L_i, \quad (2)$$

where N — the total number of servers in the network.

Table 1

Priority levels by request types

Request type	Response time requirement	System significance
Emergency medical alert	< 100 ms	Yuqori (hayotiy)
Online payment	< 200 ms	Yuqori (moliyaviy)
Video upload	< 500 ms	O'rta
Statistical report	< 2000 ms	Past

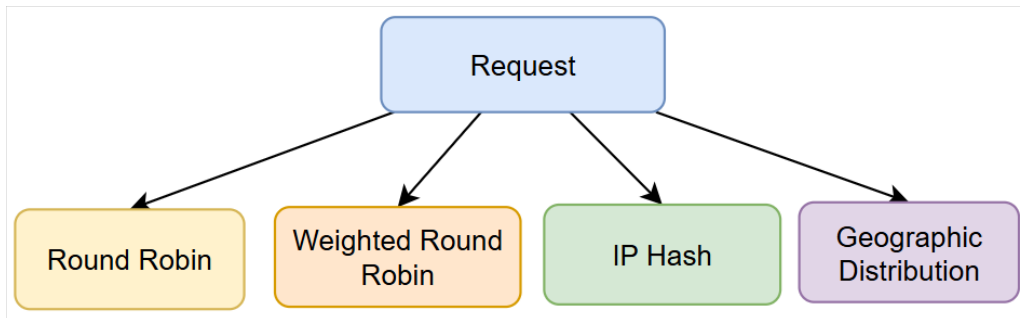


Fig. 2. Static load distribution algorithms

The smaller the variance value, the more balanced the load distribution within the system. Conversely, an increase in variance indicates greater disproportionality in resource utilization and a higher degree of load imbalance.

The requirements for system response time and the semantic significance of user requests vary considerably across different contexts. For instance, real-time processing requests—such as those in medical or financial services—demand high processing speed and minimal latency from the system, whereas informational or analytical requests impose relatively less stringent timing requirements. These distinctions are summarized in Table 1.

The problem of efficiently distributing request flows in information systems is addressed through a variety of algorithmic approaches. These approaches are generally classified into static and dynamic types, depending on their operational principles and responsiveness to system conditions. This classification, on the one hand, defines how an algorithm reacts to changes within the system, and on the other hand, determines the nature of the information it relies on during the decision-making process.

Static request flow distribution algorithms are typically designed based on predefined conditions established before the system operation begins and rely on general information about the servers—such as their computational capacity or number of connections (Fig. 2). These algorithms operate according to fixed rules and do not account for variations in system load; therefore, they yield effective results only under stable load conditions.

One of the most widely used classical approaches to request distribution is the Round Robin algorithm (Fig. 3).

In this method, incoming requests are distributed sequentially and cyclically among the available servers. The RR algorithm was originally developed in the 1960s for multi-user systems and continues to be extensively applied in network load balancers and operating systems today. According to Cisco (2023), more than 75 % of modern load balancing systems are based on RR or its modified versions.

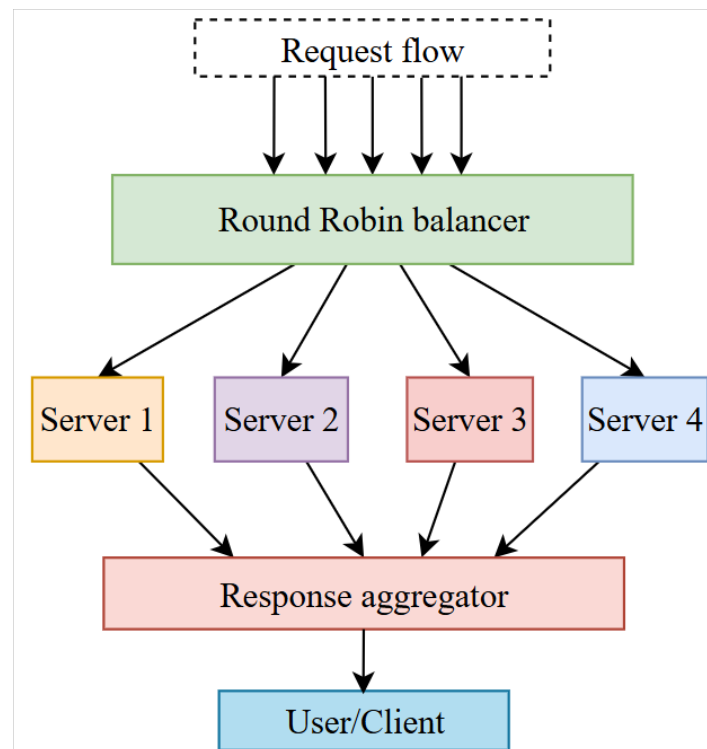


Fig. 3. Mechanism of the Round Robin algorithm

To enhance the efficiency of request flow management and distribution in information systems, it is essential to conduct an in-depth analysis of system parameters, identify their interdependencies, and employ intelligent approaches that account for uncertainty. This paper introduces a fuzzy logic-based mechanism for managing request flows through the linguistic modeling of server parameters. In the proposed model, the principle of sensitivity quantification is applied during the fuzzification stage to select appropriate membership functions corresponding to server characteristics, thereby enabling the optimization of overall system sensitivity. As a result, the system can evaluate its state in an imprecise yet semantically consistent manner, improving the effectiveness of decision-making and request distribution under uncertain conditions.

1. Methodology. Information theory provides a scientific foundation for the use of mathematical modeling in evaluating system reliability, quantitatively analyzing risk levels, and monitoring sensitivity. This approach enables the optimization of system performance by mathematically expressing stability and risk management mechanisms. In particular, the principles of Information Theory proposed by Claude Shannon (1948) and Warren Weaver remains a fundamental framework for analyzing system reliability and efficiency [14]. Their methodology allows for the statistical evaluation of key operational parameters, such as risk coefficients (probabilistic indicators) and the system's response speed to failures (e.g., recovery times), providing a quantitative basis for assessing the robustness and adaptability of complex information systems.

In the process of distributing requests across servers using fuzzy logic based systems, the fuzzification and aggregation of membership functions play a crucial role. For such systems to operate efficiently, it is essential to select appropriate membership functions corresponding

to low, medium, and high states. In fuzzy logic systems, evaluating the sensitivity of input parameters is vital to ensure optimal system performance. During the sensitivity assessment process, even small variations in the parameters of membership functions can significantly affect the system's output results. Thus, addressing this issue remains a key factor in enhancing the effectiveness of fuzzy logic systems.

The sensitivity of membership functions has also been evaluated using the nonlinear regression method [15]. The authors emphasized the high efficiency of this approach in analyzing sensitivity within fuzzy logic systems. The nonlinear regression technique was applied to determine the activation levels of membership functions within the FLS structure and to assess their sensitivity indicators, thereby contributing to an improvement in the accuracy and adaptability of the overall model.

Furthermore, studies conducted on Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have analyzed the sensitivity and stability of such systems [16–17]. Researchers developed methods to ensure optimal system performance by examining the sensitivity levels of input parameters. As a result of this approach, the flexibility of the model increased, and the accuracy of output results was significantly improved.

The process of selecting membership functions has a direct impact on the dynamic characteristics of a fuzzy logic system. This selection serves as a critical factor determining the system's overall efficiency, stability, and decision-making accuracy. If membership functions are chosen incorrectly or do not correspond to the inherent characteristics of the system, it may lead to uncertainty, misclassification, and prediction errors during the decision-making process. Consequently, the system's performance efficiency decreases, and the stability of output results deteriorates. Therefore, it is essential to consider the parametric sensitivity of the system and optimally adapt the membership functions to ensure reliable and precise operation.

In this study, the proposed combinational approach—which involves applying triangular, trapezoidal, and Gaussian membership functions according to the operational state of each server—is aimed at ensuring the optimal sensitivity level of the system. Specifically, under low-load conditions, the triangular membership function is utilized due to its simplicity and rapid responsiveness. For medium-load conditions, the trapezoidal membership function is employed, as it enables smooth transitions between operating states while maintaining the stability of the system. In contrast, under high-load conditions, the Gaussian membership function is adopted because it provides high accuracy and sensitivity, thereby reducing uncertainties within the system. Consequently, this combinational selection strategy enhances the overall adaptability, robustness, and precision of the fuzzy inference process.

Each membership function provides the most appropriate response to the corresponding operational state of the system through its mathematical form and sensitivity parameters. In this way, the combinational approach enables balanced and adaptive management of the request flow by considering such parameters as server load level, response time, resource utilization coefficient, and operational efficiency.

The analytical stages of this combinational approach are illustrated in Fig. 4. In the figure, the sensitivity levels for the triangular, trapezoidal, and Gaussian functions are explicitly defined, demonstrating how each function operates to ensure system efficiency under different conditions. This diagram provides a clear conceptual understanding of how to apply the appropriate method for selecting the optimal sensitivity level corresponding to each system state.

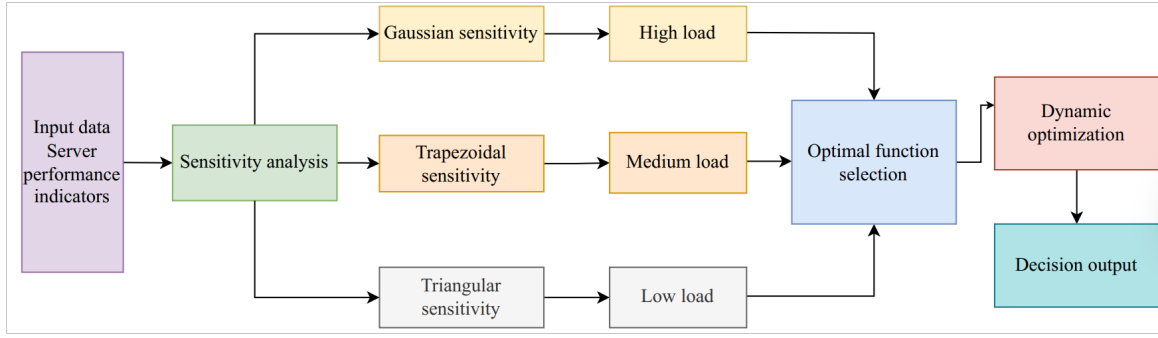


Fig. 4. Stages of combinational sensitivity analysis in the selection of membership functions

During the evaluation process of the combinational approach, various combinations of membership functions are analyzed with the aim of enhancing the overall sensitivity of the system, and the most efficient configuration is subsequently selected. Each function — triangular, trapezoidal, and Gaussian — exhibits a distinct influence on the sensitivity level based on its mathematical characteristics. Therefore, to ensure the system operates with optimal sensitivity, it becomes essential to perform both normalization of sensitivity indicators and an optimization procedure to achieve the most effective balance among these functions.

The normalized sensitivity index is one of the key indicators used to evaluate the overall sensitivity of a system. This index allows for a comparative assessment of sensitivity levels across different system states and determines the range of their variation. For each state, both the maximum and minimum sensitivity values are considered, which together serve as the basis for assessing the system's overall stability and adaptability.

The mathematical representation of the normalized sensitivity index is as follows:

$$S_{norm} = \frac{1}{3} \sum_{k=1}^3 \frac{S_i - S_{min,k}}{S_{max,k} - S_{min,k}}, \quad (3)$$

where S_k — sensitivity level for each state; $S_{max,k}$ — maximum sensitivity for each state; $S_{min,k}$ — minimum sensitivity for each state; S_{norm} — normalized sensitivity index.

This formulation implies that the normalized sensitivity index accounts for the quantitative differences among the sensitivity values corresponding to each operational state of the system and evaluates their relative proportions in a normalized manner. Such an analytical approach enables a comprehensive assessment of the system's overall sensitivity level and provides a foundation for its mathematical optimization.

As a result, the comparative evaluation of maximum and minimum sensitivity values contributes to reducing systemic uncertainty, achieving a balanced sensitivity distribution, and enhancing the overall efficiency of adaptive control mechanisms. Hence, the S_{norm} index serves as a fundamental quantitative criterion for the integrated evaluation of the system's sensitivity state, ensuring the stability, robustness, and adaptability of its functional performance.

Applying the combinational approach in analyzing the sensitivity level of each membership function enables the identification of the most effective function for achieving optimal performance. This approach contributes to the normalization of the system's overall sensitivity, allowing the optimization of sensitivity in each operational state. Furthermore, within the decision-making process, it becomes essential to monitor the system's sensitivity parameters

Table 2

Sensitivity levels and normalized sensitivity index for different approaches

Approach	Low	Medium	High	S_{norm}
Only Triangular	0.92	0.65	0.58	0.717
Only Gaussian	0.61	0.72	0.91	0.747
Combinational	0.95	0.88	0.93	0.920

and select appropriately combined functions that ensure maximal performance and adaptive response.

The evaluation of the combinational approach facilitates smooth system operation, minimizes uncertainty, and enhances overall sensitivity. As a result, the system maintains efficient performance under varying conditions, improves predictive accuracy, and reduces response time, thereby achieving a higher degree of stability and adaptability.

The results of the calculations based on different membership functions' sensitivity levels and the S_{norm} expression used to evaluate the overall system sensitivity are presented in Table 2. This table demonstrates how the S_{norm} value reflects both the system's general sensitivity and its optimal operational performance. A higher S_{norm} index indicates an improvement in the system's sensitivity optimization, enhances the effectiveness of the decision-making process, and contributes to better management of request flows within the system.

Evaluating the reliability of the proposed combinational approach plays a crucial role in ensuring the optimal and stable operation of the system. In information systems, reliability refers to the system's ability to maintain continuous operation under the influence of various internal and external factors. Therefore, reliability is regarded as one of the key indicators for assessing and predicting the performance efficiency of complex systems.

The primary objective of system reliability evaluation is to determine how consistently the system performs under different load conditions, as well as to identify potential risk scenarios and assess the system's ability to manage them. In this process, it becomes essential to mathematically model the interdependence between the system's risk coefficient α_k and the sensitivity–reliability interaction parameter β .

Within this framework, the overall system reliability is expressed through the following general mathematical relationship:

$$R_{system} = \prod_{k=1}^3 (1 - \alpha_k \cdot e^{-\beta S_k}), \quad (4)$$

where α_k — the weighting coefficient of the k -th component; β — the system's criticality parameter; S_k — the load factor affecting the k -th component; $e^{-\beta S_k}$ — represents the conditional probability of component failure under the given load.

The study examined the problem of evaluating the reliability of server systems and optimizing their sensitivity levels. In the proposed model, the interrelationship between external load factors affecting the server, the reliability of its components, and sensitivity indicators was thoroughly analyzed. These parameters play a critical role in ensuring the stable operation of the server system and effectively managing potential risk factors.

Shannon's information theory, which focuses on assessing the interaction between signal and noise within a system, primarily addresses issues related to entropy and information loss during

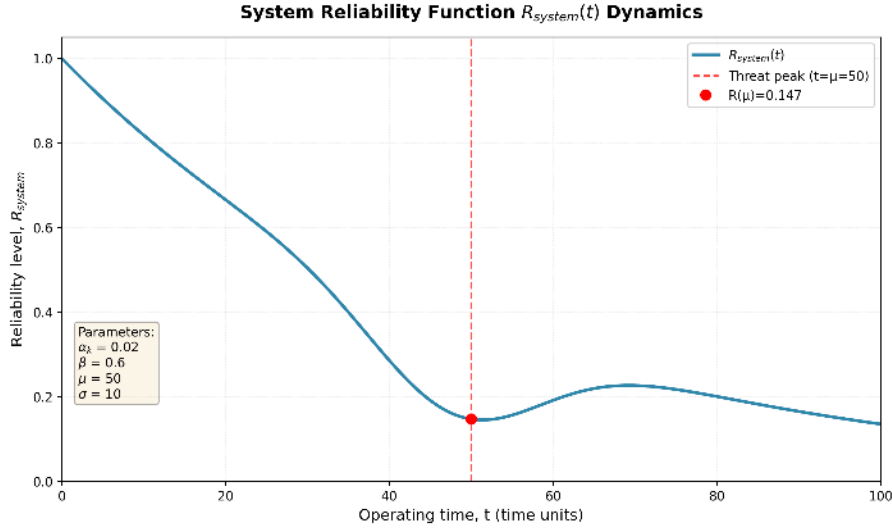


Fig. 5. Reliability function of the system over time

data transmission. However, this approach cannot directly capture the reliability, sensitivity, and stability of server systems operating under risk conditions. The Shannon model does not account for the system's dynamic response to stress factors such as load intensity, resource constraints, or latency. Consequently, it is not fully applicable to complex technical systems where sensitivity optimization, stability maintenance, and risk management are of fundamental importance.

In the present study, a model aimed at evaluating the system's reliability level, sensitivity coefficient, and response to risk impact was employed. As a result, the system's sensitivity level under risk conditions and its reliability parameters are assessed in an optimized manner. The overall reliability level of the system is determined using the following equation:

$$R_{system} = e^{-\alpha_k t} \cdot \left(1 - \beta e^{-\frac{(t-\mu)^2}{2\sigma^2}} \right), \quad (5)$$

where α_k — denotes the failure rate of the k -th component, i. e., the probability of component failure per unit of time; t — represents the operational time or the duration of the system's activity; β — maximum amplitude of risk, indicating the highest intensity of potential risk over time; μ — corresponds to the mean time of risk occurrence, representing the time interval during which the probability of system malfunction is the highest; σ — denotes the dispersion coefficient of the risk parameter, reflecting how widely the risk is distributed over time.

The variation dynamics of the system reliability function R_{system} with respect to the time factor are illustrated in Fig. 5.

Initially, the system operates with a high level of reliability; however, over time, the reliability level gradually decreases due to factors such as component aging or increased load. During the average load period ($t \approx \mu t$), the system's reliability indicator undergoes the most significant change. This situation clearly demonstrates the interrelation between the system's sensitivity parameters and risk coefficients, reflecting how variations in risk exposure directly affect the overall reliability behavior of the system.

2. Results. In the process of managing the query flow based on fuzzy logic, a series of systematic tests were conducted to evaluate system reliability by adapting server parameters

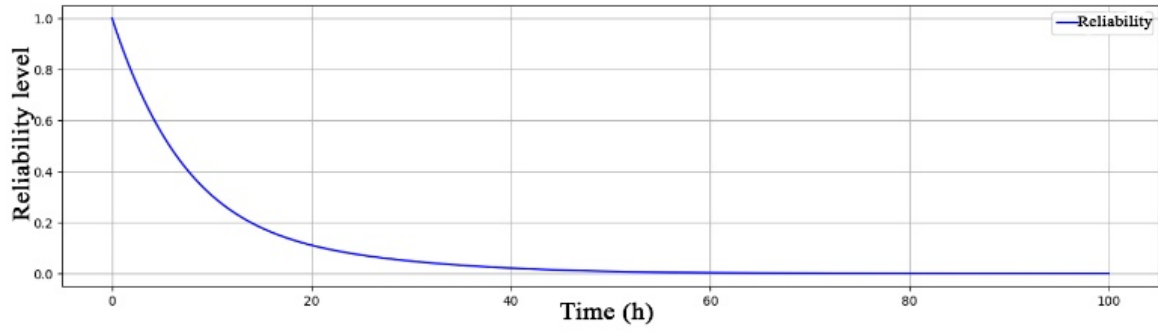


Fig. 6. Reliability dynamics for the triangular membership function

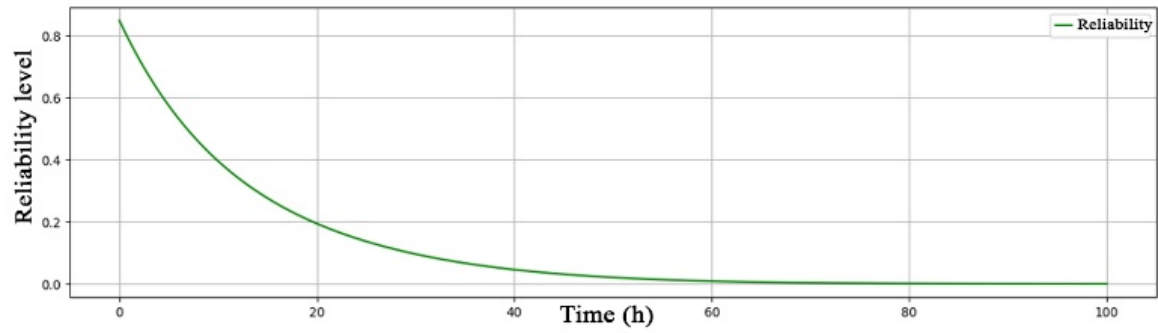


Fig. 7. Reliability dynamics for the trapezoidal membership function

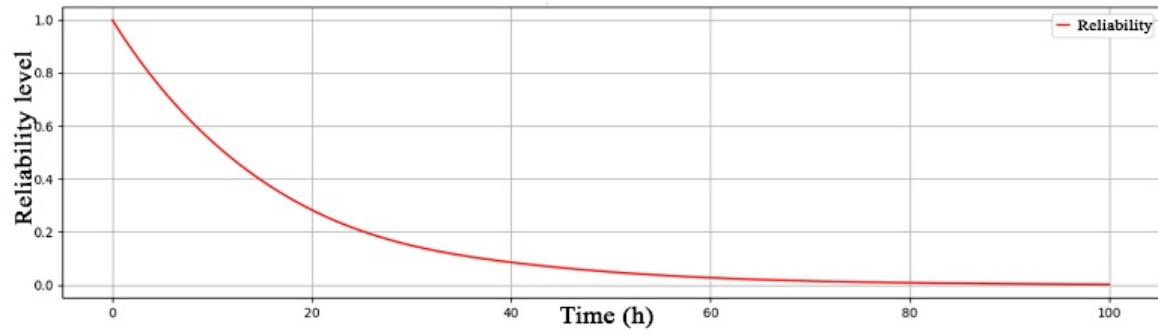


Fig. 8. Reliability dynamics for the Gaussian membership function

to the corresponding linguistic variables. The outcomes of these tests were recorded separately for each membership function. Initially, the system was tested using the triangular membership function, and the corresponding results are illustrated in Fig. 6.

For stable operating conditions, the tests were performed with the trapezoidal membership function, and the obtained results are presented in Fig. 7.

For high-load conditions, the tests were carried out using the Gaussian membership function, and the results are shown in Fig. 8. These findings are particularly important for assessing the system's sensitivity in managing the query flow under conditions of uncertainty and heavy workload.

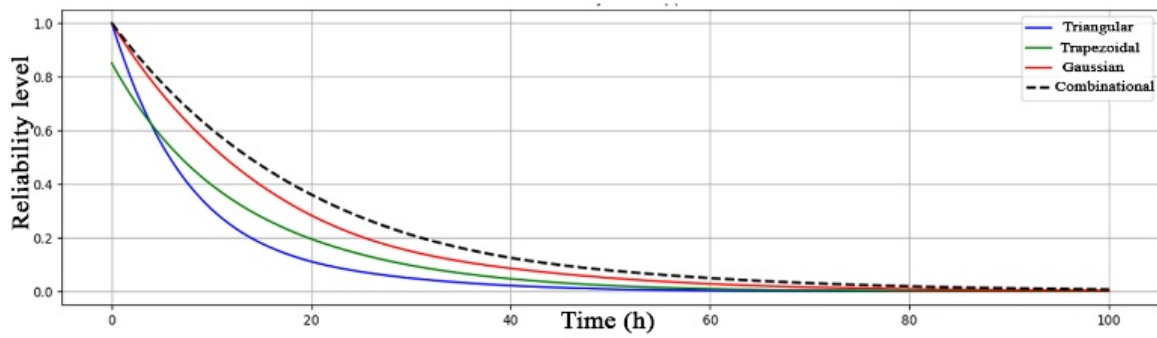


Fig. 9. Reliability dynamics for the Gaussian type membership function

Table 3

Reliability results for different membership functions

Membership function	α_k	β	S_k	R_{system}
Triangular	[0.2, 0.3, 0.5]	0.1	[0.92, 0.88, 0.93]	0.587
Trapezoidal	[0.25, 0.35, 0.45]	0.1	[0.90, 0.85, 0.91]	0.587
Gaussian	[0.15, 0.25, 0.35]	0.1	[0.95, 0.92, 0.94]	0.587
Combinational	[0.18, 0.28, 0.38]	0.1	[0.93, 0.89, 0.92]	0.587

Additionally, under increased load conditions, further evaluations with the Gaussian-type membership function were conducted, the results of which are presented in Fig. 9. These results emphasize the significance of analyzing the system's adaptive response and robustness when operating under unstable or uncertain environments, providing deeper insights into the fuzzy-based reliability control mechanism.

The reliability results calculated for each membership function are presented in Table 3. This table provides the basis for analyzing the system's reliability levels under different operational conditions, as well as for identifying the influence of risk and sensitivity parameters on the system's overall performance. The obtained results serve as a significant scientific foundation for the optimization of the system and ensuring its stable and reliable operation.

In this study, particular attention was devoted to evaluating the sensitivity of membership functions during the fuzzification stage and to optimizing their aggregation states. The appropriate selection of membership functions for low, medium, and high conditions plays a crucial role in ensuring the system's efficient performance. Therefore, the chosen combinational approach allowed achieving optimal sensitivity for each linguistic state of the system, which in turn enhanced both its stability and overall effectiveness.

The sensitivity of membership functions is a fundamental factor in managing uncertainties within the system, as even minor variations in parameters can have a significant impact on the output results. Through the implementation of an optimal combinational strategy, the uncertainties arising in the decision-making process are minimized, thereby improving the system's overall operational efficiency and robustness.

Conclusion. The study demonstrated that applying a single type of membership function to all input parameters reduces the system's sensitivity and limits decision accuracy. Therefore, an approach combining triangular, trapezoidal, and Gaussian functions—selected according to the semantic characteristics of the parameters—was developed. This approach ensured

higher sensitivity and discriminative capability in fuzzy systems, minimized uncertainty in the decision-making process, and enhanced overall system stability. Experimental results confirmed that the combinational approach outperforms traditional methods by reducing response time, balancing server load, and increasing decision accuracy. Consequently, selecting membership functions based on semantic relevance significantly improves system efficiency.

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