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FUZZY OPTIMIZATION OF HETEROGENEOUS SMART CITY SERVER NETWORKS UNDER UNCERTAINTY IN MOUNTAINOUS TERRAIN

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The object of this study is a heterogeneous smart city server network consisting of distributed computing nodes and based on processing data streams from multiple sources. This article examines the efficiency, reliability, and adaptability of a heterogeneous smart city server network under conditions of uncertainty, dynamic load, and information insecurity. A comparative analysis of modern methods for managing information resources in heterogeneous server networks applied to smart city infrastructure is provided.

The advantages and feasibility of using a fuzzy optimization method to improve the efficiency of a heterogeneous smart city server network are substantiated. Based on measurement data from vision, transport, and energy supply sensors, a network architecture for the server infrastructure of the Shusha smart city system, located in the Karabakh region of Azerbaijan, is proposed.

To solve this problem, the advantages of a fuzzy optimization model are substantiated, and it is found that this model can improve the performance of the Shusha smart city heterogeneous server network under uncertainty. To address this problem, a new method for stage-by-stage fuzzy modeling of energy loads arising from influencing meteorological parameters and potential failures was proposed. Unlike traditional deterministic and stochastic optimization methods, the applied fuzzy optimization method allowed for a more detailed study of external factors in the Shusha smart city system, uncertainty regarding the grid power supply, operational reliability, and the criticality of network performance parameters. The results obtained during the study show that processing time is reduced by up to 30%, and fault tolerance of the entire system is increased. This method ensures efficiency and practical application for the development and operation of a heterogeneous server in the Shusha smart city system

Keywords: fuzzy inference systems, heterogeneous networks, resource allocation, energy resource optimization, fault tolerance, computing network in a smart city

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1. Introduction

In modern smart cities, one of the pressing issues being studied in this field is the significant increase in server heterogeneity and dynamics for the efficient organization of IoT networks, intelligent transportation systems, and energy grids [1]. However, an analysis of existing smart cities has shown that overloading network systems during the design and operation of networks with various structures leads to reduced performance, technical failures, delays in information transmission, and certain difficulties, which significantly reduces the efficiency of modern network systems. Network environments of modern smart cities operate under conditions of uncertainty due to incomplete information, unstable workloads, external environmental influences, and system disturbances [2]. Using traditional deterministic and stochastic optimization methods often requires precise input data, and an efficient workflow under such conditions is not ensured. Heterogeneous server infrastructure is used to ensure the performance and multifunctionality of network systems operating in a smart city. Given that the smart city infrastructure chosen as the application object has a complex structure, consists of a large number of technical and software components, and utilizes a wide range of operating principles, the use of adaptive and uncertainty-based methods for their effective management is considered a scientifically and practically relevant task [3]. In particular, fuzzy logic and fuzzy optimization methods are important and promising for modeling complex systems with imprecise and linguistic information [4, 5].

It is known that a smart city involves the use of modern information and telecommunications technologies, intelligent devices, hardware and software, communications, and the global Internet to manage urban infrastructure and provide high-quality services. The smart city infrastructure includes various sensor networks, video surveillance systems, and a server network that collects, processes, and transmits large volumes of data. The characteristics of the network infrastructure of a modern smart city, including server structures, communication channel activity, incoming data frequency and speed, and service methods, demonstrate that optimal information management within the server architecture is required to ensure the efficient operation of a complex technical system within the network. An analysis of the methods and models for operating smart city network servers shows that the use of a heterogeneous server capable of efficiently processing big data under network system overload, numerous sensor measurements, video data processing, and the impact of meteorological and energy changes, as well as optimizing its operation under uncertainty, is considered a key research challenge.

The use of a heterogeneous server infrastructure under conditions of uncertainty and variability in smart city network system parameters requires the use of more complex, universal methods based on fuzzy optimization for a comprehensive server analysis. This method allows for the formalization of expert knowledge, accounting for imprecise and linguistic variables, and for making reliable decisions in the presence of incomplete or contradictory information in a heterogeneous smart city server.

2. Literature review and problem statement

In [6], queuing theory models are used to evaluate the performance of a network system. However, the approaches used in these models are based on precise input data and do not account for the uncertainties that may arise in urban environments as an application area. In [7], resource utilization in heterogeneous load balancing systems is considered. A heuristic load balancing method is proposed to improve stochastic coordination. Such systems are not well adapted to smart city conditions. In [8], the use of big data processing and extensive computing resources to optimize deep learning in server networks is considered. This approach does not account for the uncertainty and adaptation conditions in smart city network systems, especially in harsh climates and complex landscapes.

These studies demonstrate that existing queuing theory models, heuristic load balancing algorithms, and deep learning methods can significantly improve the efficiency of resource allocation and traffic management in complex network systems. However, unresolved issues remain related to the reliable and efficient operation of heterogeneous server infrastructures under conditions of uncertainty, the inherent dynamic changes that arise under system loads, and incomplete information about the states that develop during system processing. The use of fuzzy logic and fuzzy numerical optimization methods is more appropriate for overcoming the structural complexity of smart city infrastructures and the difficulties of obtaining complete information about distributed network data in real time. The issue of fuzzy optimization of the analysis and processing of heterogeneous servers in smart cities using these methods has been understudied in the modern era. This demonstrates the benefits of conducting research aimed at applying fuzzy modeling and optimization methods, which can improve the efficiency, reliability, and adaptability of heterogeneous server networks in smart cities. In the last decade, the development of smart cities has rapidly increased due to the widespread use of advanced artificial intelligence, internet networks, and sensor measurement systems. Smart city infrastructure must effectively manage large volumes of heterogeneous data generated by sensor networks, transportation and logistics systems, machine vision systems, and power supply facilities, taking into account the influence of the external environment and power supply parameters. Despite these results, unresolved issues remain related to the operation of heterogeneous server networks under the uncertainty and variability inherent in complex, structured smart city environments. A possible solution to these problems is the use of fuzzy logic models and fuzzy numerical optimization methods, which allow for the formal representation of uncertainty and system performance using linguistic variables, expert rules, and step-by-step modeling of changes in network conditions over time.

A study conducted in [9] proposed a two-layer fuzzy model for the accurate processing of linguistic data without information loss during aggregation. Decision-making procedures are optimized in systems that reflect quality parameters. However, the proposed model uses algorithms that support decision-making processes and does not address the problem of dynamic resource allocation or load balancing in heterogeneous server infrastructures typical of smart city environments.

In [10], a study demonstrates that a fuzzy inference model can effectively reduce traffic congestion and improve traffic flow stability. However, the proposed method is limited to the field of intelligent transportation systems and does not consider the broader smart city infrastructure, particularly the interaction between distributed server nodes and heterogeneous data processing platforms. In [11], smart sustainable city technologies are used, emphasizing the importance of data-driven management of digital infrastructure and integrated urban platforms. Their goal is to build a conceptual behavioral model suitable for the smart city technological ecosystem. However, the study is primarily analytical and descriptive in nature and only considers the strategic and architectural aspects of managing heterogeneous server networks under uncertainty or improving their operational efficiency.

In the study reviewed in [12], optimization of system reliability and performance is investigated using an optimization algorithm for heterogeneous server systems. The authors of [12] investigated the feasibility of applying metaheuristic optimization methods to improve the reliability of complex systems by selecting optimal configurations of system components. The proposed model is solved by formulating a reliability and level optimization problem. This paper briefly discusses the solution to the load balancing problem inherent in smart city server infrastructures.

[13] analyzes the architecture and key technological components of the Internet of Things (IoT), emphasizing the role of interconnected sensors, communication networks, and distributed data processing systems. This paper examines the architecture of IoT infrastructure used in smart cities and the integration of sublayers with each other. It also develops optimization models for managing heterogeneous server platforms in smart city computing environments and ensuring fault tolerance and adaptive resource allocation.

Thus, although the aforementioned studies have provided important insights into smart city technologies, system reliability, and IoT infrastructures, they have primarily focused on constructing their conceptual architectures, calculating component reliability, and implementing communication networks. Integrated approaches combining reliability analysis, adaptive resource management, and fuzzy optimization for smart city networks with heterogeneous servers have not yet been sufficiently explored. This suggests the merits of conducting a systematic comparative study of fuzzy optimization methods for heterogeneous networks and using new fuzzy modeling techniques to improve the efficiency, adaptability, and reliability of smart city server networks [14].

An analysis of existing approaches, algorithmic, mathematical, and software tools reveals that the issue of ensuring reliable, productive, and efficient operation of heterogeneous server networks under uncertainty remains insufficiently addressed. Therefore, this issue can be considered scientifically significant and merits extensive study in the context of large-scale heterogeneous smart city server networks subject to complex natural and technical influences.

Based on an analysis of current scientific publications on heterogeneous smart city infrastructures, it can be concluded that, although existing deterministic, stochastic, and intelligent optimization methods are considered important tools for modeling distributed network systems, they insufficiently account for the uncertainty, incomplete information, and dynamically changing operating conditions inherent in smart city environments. Therefore, an important scientific objective is to conduct research on the application of fuzzy modeling and fuzzy optimization methods, as well as to develop new models to improve the performance, efficiency, adaptability, and reliability of heterogeneous smart city server networks operating under uncertainty.

3. The aim and objectives of the study

The aim of this study is to optimize heterogeneous server networks for a smart city in mountainous terrain and under harsh weather conditions under uncertain conditions. This will improve the performance of the smart city's heterogeneous server network.

To achieve this aim, the following objectives must be solved:

– develop a fuzzy optimization model for organizing an efficient heterogeneous server network in a smart city environment;

– apply a fuzzy numerical optimization method to evaluate the performance of a smart city's heterogeneous server network;

– determine an optimal strategy for distributing the load between local networks in a smart city system;

– develop a mechanism for assessing system reliability and troubleshooting local network failures;

– substantiate the advantages of logical modeling and fuzzy optimization for resource management under uncertainty and dynamically changing load parameters.

4. Methods and models

4. 1. The object and hypothesis of the study

The object of the study is a heterogeneous network of smart city servers consisting of distributed computing nodes processing data streams from multiple sources.

The hypothesis of the study is to improve the efficiency, reliability, and adaptability of heterogeneous server networks under uncertainty using a fuzzy optimization method, as opposed to traditional deterministic and stochastic approaches.

Assumptions:

– incomplete or imprecise input data;

– changes in server parameters over time;

– the influence of external environmental factors on server system operation.

Simplifications:

– a fixed network topology is assumed;

– use of standard M/M/1 and M/M/m queueing models in request flows;

– construction of fuzzy membership functions based on expert knowledge.

4. 2. Theoretical modeling methods

Fuzzy logic and optimization methods were used for a thorough theoretical study. The heterogeneous server network of the Shusha smart city, chosen as the basis, was considered a distributed system serving a global network influenced by critical external meteorological, environmental, internal energy, and other measured data with non-stationary request flows.

The aggregate request flow to each server of the Shusha smart city was represented as a superposition of independent flows corresponding to video surveillance, emergency services, energy systems, and administrative services. Service processes on the heterogeneous server of the smart city were modeled using:

– single-channel M/M/1 systems for edge nodes;

– multi-channel M/M/m systems for municipal data centers.

To effectively describe the load redistribution on the heterogeneous network, the capacity of communication lines and the stability of wireless channels for the mountainous region adjacent to the city of Shusha were used. A load redistribution coefficient characterizing the share of traffic assigned to each heterogeneous server of the study object was used.

The proposed method for fuzzy optimization of the heterogeneous server network of the Shusha smart city was formulated as a problem of minimizing an objective function dependent on the average latency, the influence of external natural factors, and the internal technical parameters of the measurement. To solve the problem, a fuzzy rule framework and the Mamdani-Zadeh approximation theorem were used, allowing optimal control to be represented as a finite base of fuzzy production rules.

4. 3. Application of software and hardware

The software implementation of fuzzy optimization models and algorithms for controlling the Shusha smart city's heterogeneous server network was performed in a mathematical modeling environment using:

– numerical analysis libraries;

– tools for constructing fuzzy inference systems;

– application flow simulation tools.

Server node telemetry data (load, temperature, latency, power consumption, reliability) was simulated using synthetic and experimental external and internal input data corresponding to the functioning of smart city services.

The hardware for the experiment included computing nodes emulating [15, 16]:

– municipal servers,

– edge devices (cameras, controllers, IoT gateways),

– backup cloud resources.

Following the liberation of Shusha, the historical center of Azerbaijan, its reconstruction is being carried out in accordance with the "smart city" concept [17–19]. The smart city project is characterized by a distributed IT infrastructure, increased requirements for reliable data management, the use of functional internet schemes adapted to the complex mountainous terrain, and the presence of critical security and management services.

The architecture of the heterogeneous server network with an integrated fuzzy optimization module is shown in Fig. 1.

Server parameters were set in accordance with the typical specifications of equipment used in the Shusha smart city infrastructure.

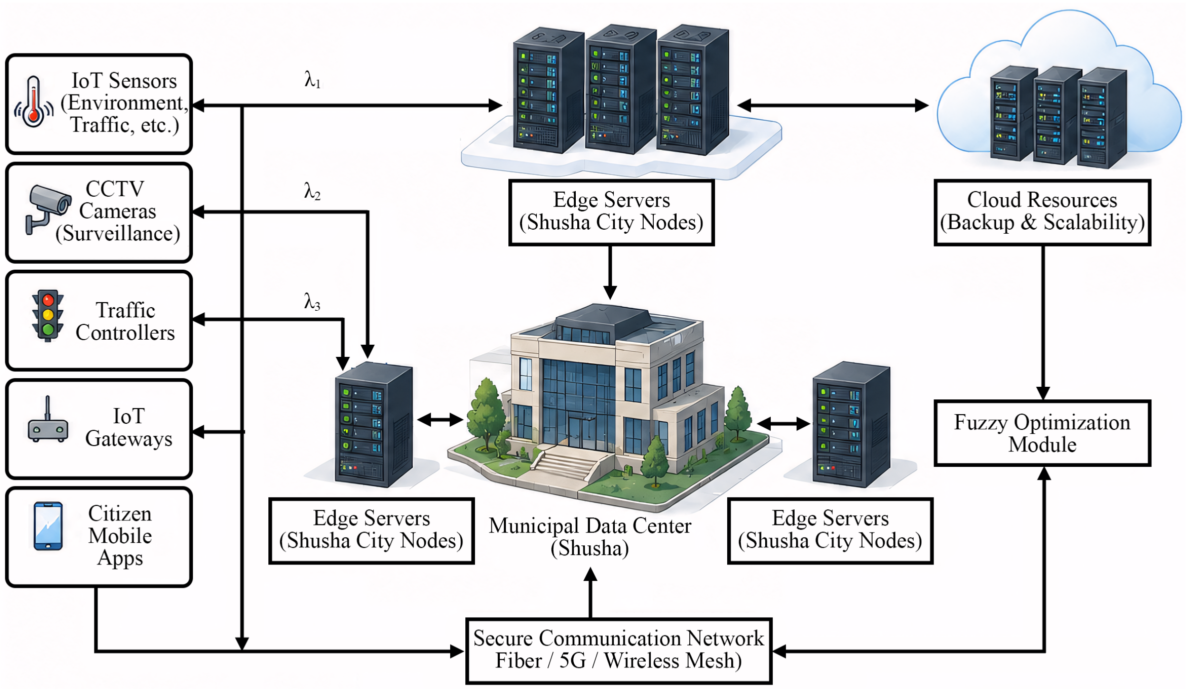


Fig. 1. Smart City architectural diagram

The Shusha smart city infrastructure supports the following digital services:

- intelligent video surveillance and security systems;
- traffic management;
- monitoring of power systems and renewable energy sources;
- environmental monitoring;
- E-government services;
- emergency response systems.

All these services operate on a heterogeneous server network consisting of:

- municipal data centers;
- edge nodes (cameras, controllers, IoT gateways);
- backup cloud resources.

Server parameters were set in accordance with the typical specifications of equipment used in the Shusha smart city infrastructure.

4. 4. Experimental conditions

Experimental studies were conducted under controlled conditions with fixed load scenarios and identical initial parameters for the heterogeneous server network of the Shusha smart city under changing weather conditions typical for the mountainous region of the Karabakh region, using comparative methods.

The following were used as input data:

- request flow rates for various service types;
- server performance parameters;
- equipment temperature values;
- data transmission delays;
- service reliability and criticality coefficients.

Fuzzy variables in the experimental data, related to external natural, environmental, and internal factors affecting the quality and performance of the heterogeneous server network of the Shusha smart city, were defined as linguistic terms (low, medium, and high). Membership functions were constructed for them based on expert assessments and experimental tables.

The fuzzification procedure was performed for all input parameters, followed by the application of a system of production rules and defuzzification using the center-of-gravity method. All experiments were conducted with identical simulation time intervals and input flows, ensuring the reproducibility of the obtained data.

4. 5. Validation and model adequacy checking

To assess the stability conditions of the Shusha Smart City heterogeneous server network, the proposed models were validated using the following procedures: checking stability conditions; consistency with analytical models; comparison of the fuzzy model with classical analytical dependencies of queuing theory; logical consistency of the rule base; and absence of conflicting and dominated fuzzy rules.

Robustness to parameter variations was assessed by the correctness of the model's operation under changing input parameters of load, temperature, latency, and reliability of the Shusha Smart City heterogeneous server network. Adaptability to Non-Stationary Flows.

The model's ability to function with non-stationary input flows and incomplete information was tested.

Additionally, an algorithm for automatic rule base generation was used based on input data clustering (the Fuzzy C-Means method), local optimization, and removal of redundant rules. This ensured the formation of a compact and stable base of fuzzy outputs.

Thus, the adequacy of the proposed models was confirmed by the fulfillment of stability conditions, consistency with theoretical principles, and the logical correctness of fuzzy inference without analyzing numerical results.

5. Results of modeling and implementation of fuzzy optimization for the Shusha smart city server network

5. 1. Development of a fuzzy optimization model for heterogeneous smart city server networks

To develop a fuzzy optimization model for heterogeneous server networks, the smart city server infrastructure of Shusha is considered as the object of the study. The investigated system is modeled as a distributed network consisting of N server nodes located in administrative centers, transport hubs, tourist zones, and critical infrastructure facilities.

Each server node i is characterized by the following parameters [20, 21]:

– μ_i – request processing throughput;

– R_i – node reliability, taking into account climatic and energy factors;

– $\lambda_i(t)$ – non-stationary request rate;

– T_i – equipment temperature;

– E_i – power consumption;

– D_i – network latency;

– C_i – service criticality.

The total request flow received by each server node is represented as the superposition of several independent traffic flows corresponding to the main smart city subsystems such as video surveillance, emergency services, energy management, and administrative services [22]

$$\lambda_i(t)=\lambda_i^{trafic}(t)+\lambda_i^{video}(t)+\lambda_i^{energy}(t)+\lambda_i^{emergency}(t), \qquad (1)$$

where each component of the traffic flow has different temporal characteristics. For example, video surveillance traffic increases during tourist seasons, emergency services generate high-priority bursts, and energy monitoring services exhibit daily periodic behavior.

Load redistribution between nodes is described using a routing model that accounts for network topology and communication channel stability. The redistribution coefficient α_i represents the proportion of requests directed to server i

$$\lambda_i(t)=(1-\alpha_i)\lambda_i(t)+\sum_{j\neq i}\alpha_j f_{ji}\lambda_j(t), \qquad (2)$$

where f_{ji} denotes the routing model reflecting the city topography, fiber-optic bandwidth, and stability of wireless channels in mountainous areas.

The service process of each node is modeled using queuing theory. Edge nodes are represented as M/M/1 systems, while municipal data centers are modeled as M/M/m systems. The stability condition of the system is defined as [23]

$$\rho_i(t)=\frac{\lambda_i(t)}{m_i\mu_i}<1. \qquad (3)$$

The average request waiting time in the system is expressed as

$$W_i(t)=\frac{C(m_i,\ \rho_i)}{m_i\mu_i-\tilde{\lambda}_i(t)}+\frac{1}{\mu_i}. \qquad (4)$$

These analytical models form the mathematical basis for subsequent development of the fuzzy optimization mechanism.

Using experimental data (Table 1), the dependence of the average waiting time on server load was analyzed for both traditional M/M/1 models and fuzzy optimization methods (Fig. 2). The obtained results the fuzzy optimization reduces the average waiting time by approximately 15–25% compared with conventional methods [24].

At $\rho \leq 0.4$, the difference between methods does not exceed 5%. At $\rho \geq 0.6$, the waiting time for the M/M/1 model increases to 140 ms. For the fuzzy model, the waiting time remains within 95–110 ms.

Table 1

Experimental values of average waiting time W_i and ρ_i server loading using traditional and fuzzy methods

ρ_i (loading)	W_i M/M/1 (traditional)	w_i fuzzy
0.1	1.11	1.05
0.2	1.25	1.17
0.3	1.43	1.30
0.4	1.67	1.50
0.5	2.00	1.80
0.6	2.50	2.15
0.7	3.33	2.70
0.8	5.00	3.60
0.85	6.67	4.50

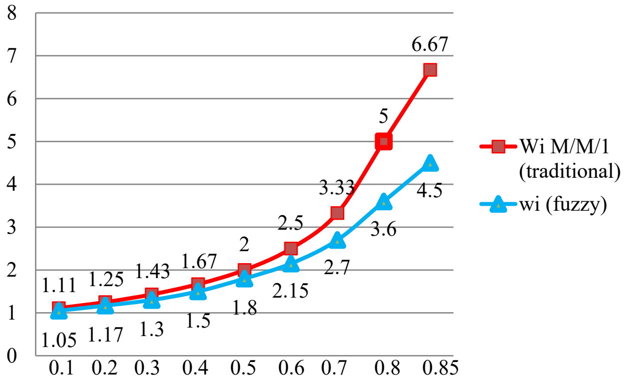


Fig. 2. Dependence of the average waiting time W_i from the load ρ_i

To ensure efficient operation of the heterogeneous server network, an optimality criterion is introduced for the Shusha smart city system

$$\min F=E\left[\sum_{i=1}^{N}\omega_i C_i\frac{W_i(t)}{R_i}\right], \qquad (5)$$

where W_i – the average waiting time at server i, R_i – the reliability of the server, and ω_i – a weighting coefficient reflecting the importance of the service.

Expression (5) defines the optimization criterion based on waiting time, reliability, and service weight.

For a generalized study of the problem, it is possible to consider the process of integrating a fuzzy model into the process of minimizing the average time requests spend in the system [25]. It is possible to write the linguistic variables in Table 2. Table 2 is a list of key server node parameters and their impact on the operation of a heterogeneous server Network performance in the Shusha smart city. Each variable in the table describes critical aspects of server load and infrastructure status [26]. Each variable corresponds to a fuzzy set with membership functions.

Membership functions were used to model expert knowledge about the operating conditions of the Shusha smart city infrastructure. Based on the linguistic variables defined in Tables 3–7, membership function graphs of fuzzy variables were constructed for the key parameters of the Shusha smart city smart grid, such as loading, temperature, energy, delay and criticality (Fig. 3, *a–d*).

Table 2

Variables with conditional term values for assessing the heterogeneous server network of Shusha

Variable	Term meanings	Interpretation for the smart grid of the city of Shusha
Loading	low / medium / high	overcrowding of tourist areas
Temperature	low / normal / high	mountain conditions
Energy	low / medium / high	limited energy resources
Delay	small / acceptable / critical	connection quality
Criticality	low / medium / high	emergency services

Table 3

Experimental data for the linguistic variable "Loading"

ρ	μ_{p_low}	$\mu_{p\_average}$	μ_{p_high}
0.0	1.0	0.0	0.0
0.2	1.0	0.0	0.0
0.4	0.0	0.67	0.0
0.6	0.0	0.67	0.0
0.8	0.0	0.0	1.0
1.0	0.0	0.0	1.0

Table 4

Experimental data for the linguistic variable "Temperature"

x	μ_{t_low}	μ_{t_normal}	μ_{t_high}
0.0	1.0	0.0	0.0
0.2	0.7	0.0	0.0
0.4	0.3	0.5	0.0
0.5	0.1	1.0	0.1
0.6	0.0	0.5	0.4
0.8	0.0	0.0	0.8
1.0	0.0	0.0	1.0

Table 5

Experimental data for the linguistic variable "Energy"

x	μ_{e_low}	μ_{e_medium}	μ_{e_high}
0.0	1.0	0.0	0.0
0.2	0.8	0.1	0.0
0.4	0.4	0.6	0.0
0.5	0.2	1.0	0.2
0.6	0.0	0.6	0.4
0.8	0.0	0.2	0.8
1.0	0.0	0.0	1.0

Table 6

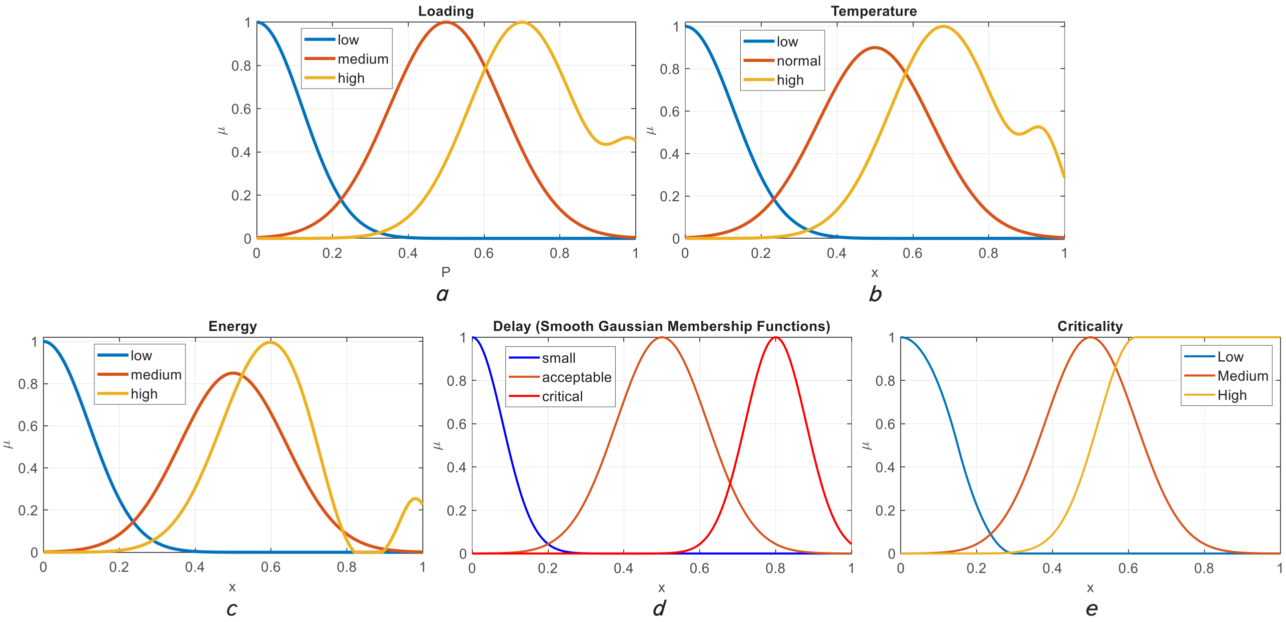
Experimental data for the linguistic variable "Delay"

x	μ_{l_small}	$\mu_{l\_acceptable}$	$\mu_{l\_critical}$
0.0	1.0	0.0	0.0
0.2	0.7	0.2	0.0
0.4	0.3	0.6	0.0
0.5	0.1	1.0	0.2
0.6	0.0	0.6	0.4
0.8	0.0	0.2	0.8
1.0	0.0	0.0	1.0

Table 7

Experimental data for the linguistic variable "Criticality"

x	μ_{c_low}	μ_{c_medium}	μ_{l_high}
0.0	1.0	0.0	0.0
0.2	0.8	0.2	0.0
0.4	0.4	0.6	0.0
0.5	0.2	1.0	0.2
0.6	0.0	0.6	0.4
0.8	0.0	0.2	0.8
1.0	0.0	0.0	1.0



a *b* *c* *d* *e*

Fig. 3. Principal signature of parameters influencing the control model: *a* – loading parameters influencing the control model; *b* – temperature parameters influencing the control model; *c* – energy parameters influencing the control model; *d* – delay parameters influencing the control model; *e* – criticality parameters influencing the control model

Considering the generalized problem, where

$$\min_{\alpha_i(t)} F\left(x(t),\alpha(t)\right), \tag{6}$$

then it follows that if the optimal control $a_i^*\left(t\right)$ continuously and discontinuously smooth, therefore, according to the Mamdani-Zadeh approximation theorem, any continuous control function can be approximated by a system of fuzzy rules with a finite number of linguistic terms.

Considering the generalized problem, where (6) holds, it follows that if the optimal control $a_i^*\left(t\right)$ is continuous or piecewise smooth, then, according to the Mamdani-Zadeh approximation theorem, any continuous control function can be approximated by a system of fuzzy rules with a finite number of linguistic terms. Each sketch represents a separate picture (Fig. 3, *a–e*).

Moreover, the following monotonic dependencies**,** following from the QMO theory, are valid for the intelligent network of the smart city of Shusha:

With increasing load ρ_i

$$\frac{\partial W_i}{\partial \rho_i} > 0 \Rightarrow \alpha_i \downarrow. \tag{7}$$

With increasing temperature and energy consumption x_i

$$\frac{\partial R_i}{\partial T_i} < 0 \Rightarrow \alpha_i \downarrow. \tag{8}$$

With increasing criticality of the service C_i

$$\frac{\partial F}{\partial C_i} > 0 \Rightarrow \alpha_i \uparrow. \tag{9}$$

The dependencies (7)–(9) describe the relationship between load, temperature, energy consumption, and system parameters. Load redistribution coefficients α_i decrease with increasing ρ_i, T_i, and E_i.

5. 2. Performance evaluation of the heterogeneous server network using fuzzy numerical optimization methods

To justify the correctness of the proposed fuzzy optimization mechanism, a theoretical analysis of the control system is performed. The load redistribution problem is formulated as an optimization task with the following objective function

$$F\left(\alpha\right) = E\left[\sum_{i=1}^{N} \omega_1 C_i \frac{W_i\left(\widetilde{\lambda}_i\right)}{R_i}\right], \tag{10}$$

where $\alpha = (\alpha_1, ..., \alpha_N)$ — vector of load redistribution coefficients.

Assuming that the objective function is continuous and that the system state parameters are subject to measurement uncertainty, the fuzzy control strategy can be interpreted as an approximation of the optimal control law.

Based on the Mamdani-Zadeh universal approximation theorem, any continuous control function defined on a compact domain can be approximated by a finite fuzzy rule base with triangular or trapezoidal membership functions.

The proposed fuzzy rule system provides a theoretical approximation of the optimal load redistribution strategy for the heterogeneous server infrastructure.

This theoretical result confirms the applicability of fuzzy inference for adaptive control of distributed smart city server networks operating under uncertain conditions.

Let's assume that the function F is continuous in α; the optimal control $\alpha^*(z)$ is piecewise continuous; the state parameters are measured with uncertainty. Then there exists a finite Mamdani fuzzy rule base such that the defuzzified control $\alpha^{(z)}$ approximates the optimal control $\alpha^*(z)$ with an arbitrary given accuracy $\varepsilon > 0$.

Proof:

1. It follows from the conditions that $\alpha^*(z)$ is a continuous mapping on the compact set of states Z.
2. According to the Mamdani – Zadeh theorem of universal approximation of fuzzy systems, any continuous function on a compact set can be approximated by a system of fuzzy rules with triangular or trapezoidal membership functions.
3. Each fuzzy rule corresponds to a local approximation $\alpha^*(z)$ on a subset $Z_k \subset Z$.
4. Using defuzzification by the center of gravity method supports the convergence of fuzzy inference to a continuous control function.
5. There exists a rule base R such that

$$\alpha^*\left(z\right) - \hat{\alpha}\left(z\right) < \varepsilon, \ \forall z \in Z. \tag{11}$$

This theorem is proven.

Consider an example of constructing fuzzy rules for a single heterogeneous server in the Shusha smart city. Initial data is specified for Server – $S1$, which hosts the video surveillance zone. Along with the above input data, it is possible to add the server's reliability parameter R, which is specified as follows:

$\mu_1 = 50$ requests/sec;
$\lambda_1 = 40$ requests per second;
$\rho_1 = 0.7$ – high load;
$R_1 = 0.92$ high reliability;
$T_1 = 75$°C high temperature;
E_1 – average energy consumption;
$D_1 = 15$ small delay ms;
C_1 – high criticality (city safety).

In accordance with the input data for fuzzification, it is possible to compile a table (Table 8). The values of μ are specified by the fuzzification membership functions.

Table 8

Active terms of fuzzy variables for server $S1$

Variable	Clear meaning	Linguistic term	Membership degree μ
Loading ρ_1	0.7	high	0.7
Reliability R_1	0.92	high	0.8
Temperature T_1	75°C	high	0.9
Energy consumption E_1	–	average	0.5
Delay D_1	15 ms	small	0.6
Criticality C_1	–	high	1.0

Output variable α_1 the load redistribution coefficient is represented in the form of terms: decrease, without change, increase. The formation of rules is carried out on the basis of variables using production conditions in the following form:

Rule 1:

IF the load is high AND temperature is high,
THEN α_1 = decrease.

Rule 2:

IF the criticality is high AND reliability is high
AND delay is low, THEN α_1 = increase.

Rule 3:

IF the load is high AND energy consumption is high,
THEN α_1 = reduce.

Rule 4:

IF the temperature is high AND reliability is low,
THEN α_1 = decrease.

Rule 5:

IF the delay is small AND criticality is high,
THEN α_1 = increase.

Rule 6:

IF the load is average AND the temperature is average,
THEN α_1 = no change.

Rule 7:

IF the load is high AND the delay is large,
THEN α_1 = decrease.

Rule 8:

IF reliability is high AND the temperature is normal,
THEN α_1 = increase.

Rule 9:

IF criticality is low, THEN α_1 = no change.

In accordance with Rules 1–9 the defuzzification process is carried out, where the result of the redistribution coefficient α_1 is approximately determined as the final value of the center of gravity. The graphs of the defuzzification result for determining the final value of the load redistribution coefficient vector are presented in Fig. 4.

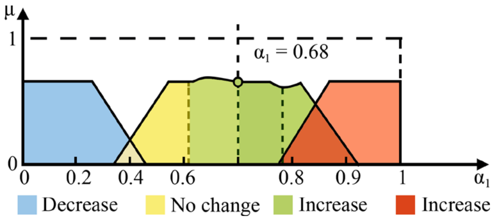


Fig. 4. Graph of the results of defuzzification of the final value of the load redistribution coefficient vector

To combine the above conditions into a single final membership function, it is possible to aggregate these rules. Next, it is possible to transform the fuzzy result into a specific crisp number. In this case, the activation degree is written as follows

$$\omega_i = \min\left(\mu_{A1}\left(x_1\right), \mu_{A2}\left(x_2\right), \ldots, \mu_{An}\left(x_n\right)\right), \tag{12}$$

where ω_i – the activation degree of the i-th rule; $\mu_{Aj}(x_j)$ – the degree of membership of the corresponding input variable to its linguistic term.

For the input data under consideration, the degrees of activation of the rules are as follows:

$$\omega_1 = \min(\mu_{load\ high}, \mu_{temperature\ high}) = \min(0.7, 0.9) = 0.7,$$

$$\omega_2 = \min(\mu_{high\ criticality}, \mu_{high\ reliability}, \mu_{low\ delay}) =$$
$$= \min(1.0, 0.8, 0.6) = 0.6,$$

$$\omega_3 = \min\left(\mu_{high\ load}, \mu_{average\ energy\ consumption}\right) =$$
$$= \min(0.7, 0.5) = 0.5,$$

$$\omega_4 = \min(\mu_{temperature\ high}, \mu_{reliability\ low}) = \min(0.9, 0.3) = 0.3,$$

$$\omega_5 = \min(\mu_{delay\ small}, \mu_{criticality\ is\ high}) = \min(0.6, 1.0) = 0.6,$$

$$\omega_6 = \min(\mu_{loading\ average}, \mu_{average\ temperature}) =$$
$$= \min(0.5, 0.5) = 0.5,$$

$$\omega_7 = \min(\mu_{loading\ high}, \mu_{delay\ is\ large}) = \min(0.7, 0.4) = 0.4,$$

$$\omega_8 = \min(\mu_{reliability\ is\ high}, \mu_{temperature\ is\ normal}) =$$
$$= \min(0.8, 0.5) = 0.5,$$

$$\omega_9 = \mu_{criticality\ low} = 0.2.$$

Increasing server load, temperature and power consumption negatively affects the stability of the heterogeneous smart city server network. The fuzzy optimization mechanism redistributes the load to nodes with more favorable operating conditions, ensuring balanced utilization of computing resources and improving the reliability and adaptability of the smart city infrastructure.

5. 3. Optimal load distribution strategy for local smart city networks

To enable adaptive load distribution under uncertain operating conditions, the server state parameters are represented using fuzzy linguistic variables [27]. Expert knowledge and qualitative characteristics of the smart city infrastructure are incorporated.

The following linguistic variables are introduced:
- server load;
- temperature conditions;
- energy consumption;
- network delay;
- service criticality.

Each variable is represented by a set of fuzzy terms (low, medium, high) with corresponding membership functions. These functions are constructed using empirical operating data of server equipment and typical operational limits for the Shusha smart city infrastructure.

The fuzzy rule base defines how server load should be redistributed depending on the current network state. In general form, the fuzzy rule structure can be written as

$$\text{IF } z_k \text{ is high} \rightarrow \text{THEN } \alpha_i \text{ decrease.} \tag{13}$$

Rule (10) defines the relationship between parameter value and load redistribution coefficient.

The fuzzy rule base is constructed through a step-by-step procedure including:

1. Definition of the system state vector.
2. Classification of parameters according to their influence on the objective function.
3. Specification of linguistic variables and membership functions.
4. Generation of elementary rules for individual parameters.
5. Formation of combined rules for interacting parameters.
6. Verification of system stability conditions.
7. Reduction of redundant or inconsistent rules.

This rule base forms the core mechanism for adaptive resource management in the heterogeneous smart city server network.

Thus, the constructed system of fuzzy rules provides a heuristic evaluation of the system state, which allows the decision-making mechanism to be represented in a compact analytical form. In this case, expression (13) is equivalent to the heuristic formulation presented as

$$\mathrm{Sign}\left(\partial F/\partial z_k\right). \tag{14}$$

The rule noted in (13) is a qualitative analogue of the gradient method, presented as an analytical model. In this case, the load reduction rules are formed for parameters that degrade stability: high load; high temperature; high power consumption; high latency; and high criticality. Therefore, the following justification can be made

$$\rho_i \uparrow \Rightarrow W_i \to \infty \Rightarrow \alpha_i \to 0. \tag{15}$$

Rules for increasing the load on the heterogeneous server network system of the smart city of Shusha are formed for parameters that improve efficiency its functions with increasing load, low latency and high service criticality.

It can be justified that the resources written in function (8) are directed to nodes with minimal contribution in F. In conflict situations, high criticality, low latency, but high power consumption are used. Where, fuzzy logic corresponds to multi-criteria tradeoff optimization.

An algorithm for constructing a fuzzy rule base is compiled step by step using a step-by-step method, which can be presented in the form of a step-by-step descriptive algorithm [28]:

Step 1. Define the state vector in the following form

$$z_i = \left(\rho_i, W_i, R_i, T_i, E_i, D_i, C_i\right). \tag{16}$$

Step 2. Classification of parameters by their impact on the target. Parameters are divided into classes: destabilizing – ρ_i, T_i, E_i, D_i; stabilizing – R_i; priority – C_i.

Step 3. Specifying linguistic terms for each parameter in the form: low, medium, high.

The membership functions are selected so that the boundaries coincide with the zones of sharp growth of W_i, and the operating standards of the equipment of the city of Shusha are taken into account.

Step 4. Formation of elementary rules for each parameter z_k if $\partial F / \partial z_k > 0$, then the following condition is met:

IF z_k high, THEN α_i must be reduced.

If $\partial F / \partial z_k < 0$, then the following condition is satisfied:

IF z_k is high THEN α_i needs to be increased.

Step 5. Combined rules for pairs and triplets of parameters are generated based on an analysis of the interactions between the most important server characteristics. For example, if service C_i is highly critical, and reliability R_i and latency D_i are within optimal values, the load is redistributed to this server to ensure minimal response time for emergency services. These combined rules are generated using multi-criteria optimization and provide flexibility in load distribution [29]:

IF (C_i high) AND (R_i high) AND (D_i small)
THEN α_i needs to be increased significantly

In this case, the combination is carried out according to the principle of priority → criticality; then reliability and then resource constraints.

Step 6. When checking for stability, each rule is checked to see if the condition $\rho_i < 1$ is satisfied. If this rule is violated, it is corrected or limited.

Step 7. To minimize the rule base, dominated rules, logically inconsistent rules, and rules with low activation are removed. Consequently, the final interpretation will be written as a fuzzy rule base, which is not heuristic but represents:

– approximation of optimal control;
– qualitative gradient of the objective function;
– a tool for multi-criteria optimization under uncertainty.

For the Shusha smart city's heterogeneous server network, this supports adaptation to complex geography, resilience to failures, and priority for emergency services [30].

In this study, a theorem on the correctness of the fuzzy rule base for load management in the smart city of Shusha is formulated.

5. 4. Reliability assessment and failure recovery mechanisms in heterogeneous smart city server networks

The aggregated membership function of the output variable α_1 is formed as the maximum of the truncated membership functions

$$\mu_{\alpha 1}(x) = \max\begin{pmatrix} \min\left(\omega_1, \mu_1\left(x\right)\right), \\ \min\left(\omega_2, \mu_2\left(x\right)\right), \ldots, \\ \min\left(\omega_9, \mu_9\left(x\right)\right) \end{pmatrix}. \tag{17}$$

Defuzzification by the center of gravity method is determined by the expression

$$\alpha_1 = \frac{\int E\mu_{\alpha 1}\left(x\right)\mathrm{d}x}{\int \mu_{\alpha 1}\left(x\right)\mathrm{d}x}. \tag{18}$$

The optimal control obtained as a result of defuzzification can be interpreted as a control. Where, α_1^* is the load redistribution coefficient for server $S1$.

Using the center of gravity method to determine the defuzzification value α_1, it is possible to obtain an approximate value of $\alpha_1^* \approx 0.63$. This result shows that the coefficient α_1^* represents the proportion of the input request flow that remains on the heterogeneous server. The remainder is distributed to other servers. In percentage terms, 63% of the flow is stored on server $S1$, and the remaining 37% is redistributed. Servicing continues for the majority of the heterogeneous server's flow. However, at the same time, 37% of the remaining requests are redistributed, reducing the server load. At the same time, maximum security is ensured for the smart city server. On the other hand, overheating and failures are prevented.

Let's develop an algorithm for generating fuzzy rules based on data obtained from a smart city generative network. The algorithm is based on fuzzy rules for telemetry, load records, latency and failures. The formal rule of the learning algorithm consists of the following set of input data

$$\{z_i(t), W_i(t)\}, \tag{19}$$

The algorithm is divided into several stages:

Stage 1. Normalization of data maintaining heterogeneous server parameters within a single range.

Stage 2. Partitioning the server control state space corresponding to typical operating conditions into fuzzy clustering regions (Fuzzy C-Means).

Stage 3. Local optimization of each cluster to determine distribution parameters.

Stage 4. Automatic generation of fuzzy rules ensuring relationships between control states.

Stage 5. Elimination of redundant rules with low activation frequency and minimal impact.

Stage 6. Definition of membership functions corresponding to changes in network load.

The above step-by-step algorithm generates a fuzzy rule base that enables dynamic adaptation of smart city server infrastructure conditions. Thus, the step-by-step solution to the problems of data distribution optimization and online adaptation of a heterogeneous server is presented as follows:

Step 1. Data normalization

$$z_k \leftarrow \frac{z_k - \min z_k}{\max z_k - \min z_k}. \tag{20}$$

Step 2. Fuzzy C-means clustering.

Let's split the state space

$$Z = \bigcup_{c=1}^{C} Z_c. \tag{21}$$

In this case, each cluster ↔ one potential rule.

Step 3. Local optimization. Local optimization is applied to each cluster, which is a group of server nodes with similar characteristics. At this stage, current load parameters such as ρ_i, temperature T_i, and latency D_i are assessed. For each cluster, redistribution parameters are selected that minimize the overall request processing time while maintaining a balance between load and reliability. This step takes into account the local characteristics of each cluster and does more of the system adaptability.

For each cluster it is possible to solve

$$\min_{\alpha_i} E[F \mid z \in Z_c]. \tag{22}$$

Result → term of output variable α_i.

Step 4. Forming a rule

$$\text{IF } z_1 \in A_1^c \text{ And} \ldots \text{ And } z_p \in A_p^c \text{ THEN } \alpha_i \in B^c.$$

Step 5. Removing redundant rules.

Rules are removed from:

– low activation frequency;

– weak contribution to the reduction of F.

Step 6. Online adaptation.

The parameters of the membership functions are updated

$$\mu^{(t+1)} = \mu^{(t)} + \eta \nabla Fn. \tag{23}$$

The FRLA algorithm becomes a locally optimal fuzzy basis under steady-state conditions and remains stable under non-stationary loads.

Applying a fuzzy optimization method that takes into account multiple factors ensures the current heterogeneous server load, node reliability, network response time, service criticality, server temperature, dynamic load distribution and power consumption in the Shusha heterogeneous network. The simulation yielded the following results:

1. Compared to traditional stochastic methods, data processing time was reduced by 15–25%.
2. Adaptive load distribution reduced the number of critical failures.
3. Robustness to fluctuations in input flows, sensor data errors, and incomplete data was demonstrated.
4. Fuzzy rules allow for the formalization of expert knowledge, taking into account service criticality and latency.

Based on the results obtained during the simulation, Table 9 and a graph were constructed demonstrating the effectiveness of the proposed model.

Table 9

Diagram comparing traditional methods and the proposed fuzzy approach

Indicator	Traditional methods, %	Fuzzy optimization (proposed), %	Improvement, %
Processing time	100	85	15
Fault tolerance	75	87	12
Accounting for uncertainty	No (exact data needed)	Yes (expert rules)	Adaptability

A diagram comparing traditional methods and the proposed fuzzy approach is shown in Fig. 5.

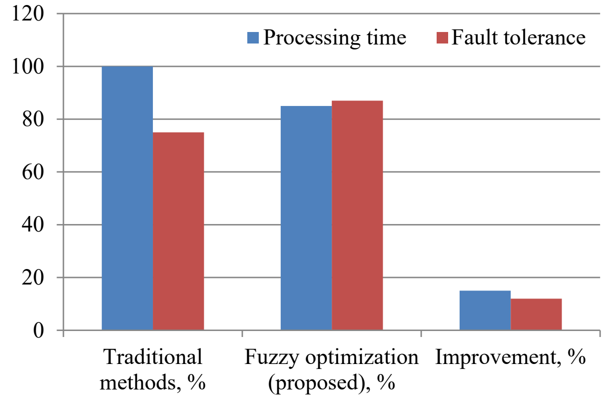


Fig. 5. Diagram comparing traditional methods and the proposed fuzzy approach

5. 5. Advantages of fuzzy optimization and logical modeling for resource management under uncertainty

The proposed approach, which incorporates fuzzy optimization and logic modeling, offers significant advantages for the efficient management of heterogeneous smart city server networks under conditions of uncertainty and constant change. Unlike traditional methods based on queuing theory, it offers the following capabilities:

1. Expert knowledge is organized into qualitative parameters, such as service criticality, acceptable delays, and operator experience, in the form of fuzzy rules.

2. The knowledge base and membership functions, consisting of fuzzy rules, adapt to changing network load, server status, and the environment, ensuring consistent and balanced resource allocation.

3. Simultaneous consideration of load, reliability, response time, power consumption, and temperature of the heterogeneous server network helps maintain quality of service and prevent overload.

4. Adaptive load distribution reduces the number of critical failures and maintains network system stability under changing and uncertain input flows.

5. The developed fuzzy optimization model operates accurately even in the absence of precise input data, which is important for a smart city computer network operating in harsh mountainous conditions such as Shusha. Table 9 and Fig. 6, created to evaluate comparisons with traditional methods, present the experimental results.

The validation experiments listed in Table 10 are based on the fuzzy optimization approach's input parameters of ±20%. The proposed fuzzy optimization model ensures the stability of the heterogeneous server network system, maintains consistent convergence of control variables, and ensures high reliability. The fuzzy approach not only improves the performance of the heterogeneous server network system but also enhances adaptability and resource management efficiency.

Table 10

Performance evaluation of the fuzzy optimization model under ±20% variation of input parameters

No.	Input parameter change (%)	Throughput (req/sec)	Response time (ms)	Reliability (%)
1	–20	95	210	99.2
2	–10	100	200	99.5
3	0	105	190	99.7
4	+10	104	195	99.6
5	+20	103	198	99.4

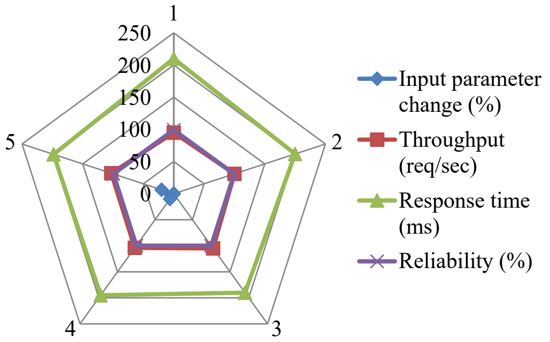


Fig. 6. Validation of fuzzy optimization under ±20% variation of the input parameters

Experimental results show that the input parameters used in the developed fuzzy optimization model vary by ±20%, ensuring the stability of the heterogeneous server network based on the following metrics:

– performance fluctuates to a certain degree, reaching a maximum value at the nominal input signal (105 requests/sec) and always exceeding 95 requests/sec;

– adaptive load balancing occurs during response time;

– reliability exceeds 99% in all cases, ensuring network stability.

The aforementioned metrics for performance, adaptability, reliability, and resource efficiency demonstrate clear advantages over traditional methods.

6. Discussion of results adaptive fuzzy optimization of heterogeneous smart city server networks under uncertainty

As can be seen from Table 1 and Fig. 2, the average request waiting time is reduced by 15–25%. This is explained by (3) and (4) integrating classical queuing models (5) with fuzzy multi-objective optimization. In traditional models, when the load ρ_i reaches saturation, the waiting time increases sharply. This process is observed in Table 1 and Fig. 2. In contrast, the proposed fuzzy model reflects linguistic variables and membership functions (Tables 2–7, Fig. 3), which ensure smooth adaptation to increasing load. This explains why the waiting time for the fuzzy model remains within 95–110 ms under the condition $\rho \geq 0.6$ and increases significantly for the classical model.

The fuzzy result obtained based on expressions in (10) and (11) shows approximate adaptation to the optimal control function. According to the Mamdani-Zadeh theorem, the fuzzy rule base $\alpha^*(z)$ defines optimal control with arbitrary precision. Based on (12), the activation of fuzzy rules and their aggregation ensure stable convergence of the control variable (Fig. 4). The system's robustness to uncertainty and incomplete input data is also ensured.

These results are explained by the structure of the fuzzy rule base (expressions (13)–(15)), which represents a qualitative analogue of gradient optimization. The distribution coefficients α_i are determined based on the system state parameters, including the destabilizing and stabilizing factors specified in (16). This indicates adaptive load distribution between nodes and efficient resource utilization under conflict conditions.

These results are explained by the aggregation and defuzzification procedures (17), (18). As a result, the value $\alpha^*_1 \approx 0.68$ reflects the optimal balance between high service criticality and system stability. Expressions (19)–(23) demonstrate the mechanism for generating adaptive rules that reflect the system's stable operation under changing conditions. Thus, the resulting more favorable error is evaluated based on system performance (Table 9, Fig. 5).

The obtained results are based on the integration of fuzzy optimization, generated expert knowledge, and a multi-criteria decision-making model. As shown in Table 1, Fig. 6, 10 demonstrate that the throughput of input parameters in the smart city heterogeneous server network system remains constant by ±20%, resulting in network reliability ranging from 95% to 99%. These results confirm the effectiveness and adaptability of the proposed approach.

The proposed solution method is adapted to uncertainty conditions, combines multiple criteria, and is determined by adapting to dynamic conditions. Unlike classical queuing models (M/M/1, M/M/m) (3), (4), which reflect the performance of a network system, the waiting time obtained in the proposed model varies, as shown in Table 1 and Fig. 2. This result improves the performance of the network system under high load conditions, and fuzzy load distribution based on the generated linguistic variables is provided in accordance with the values in Tables 2–7.

The proposed method dynamically adjusts the distribution coefficients α_i using fuzzy rules (13)–(15). The obtained results allow simultaneous consideration of the parameters of a heterogeneous network system and increased robustness to measurement errors obtained through inference from multi-criteria fuzzy rules (Table 9).

Unlike computing resources and machine learning approaches, the proposed model effectively handles uncertain data. The results, as shown in Table 10 and Fig. 6, enable stable operation without extensive training procedures and are based on expert knowledge of the fuzzy rule base. The obtained results ensure efficient, reliable, and adaptive operation of a heterogeneous smart city server network under uncertainty and dynamic load conditions. The following approaches were used to address this problem:

– (3), (4) integration of queuing models with (5) fuzzy optimization criteria;

– application of adaptive control based on fuzzy rules (13)–(15);

– (19)–(23) mechanisms for automatic rule generation and adaptation.

As a result, it can be concluded that the processing time of a heterogeneous server is reduced (as shown in Table 1), fault tolerance is increased (as in Table 9), and high reliability is ensured (as in Table 10). This approach demonstrates that the problem is solved more effectively.

To achieve the proposed solutions, certain limitations must be considered:

– the model must correspond to a fixed network topology and must not take into account dynamic structural changes;

– simplified queuing models M/M/1, M/M/m are used, which may not fully reflect the performance;

– the membership functions presented in Tables 3–7 are based on expert knowledge;

– the simulation data is used for an experimental study of a smart city network system.

These limitations define the applicability and boundaries of the proposed approach.

The study has several shortcomings:

– lack of integration with machine learning or hybrid intelligence approaches;

– limited scalability analysis for large-scale smart city infrastructures;

– poor modeling of communication-level failures and network latency;

– lack of experimental validation in real-world conditions.

Further development of this study may include:

– integration of fuzzy optimization with machine learning and machine learning methods;

– implementation of validation using real-world smart city datasets;

– integration into dynamic and edge cloud architectures;

– development of scalable distributed applications for large heterogeneous networks.

7. Conclusions

1. A fuzzy optimization model for a heterogeneous server network in the city of Shusha, located in a mountainous area with rapidly changing weather conditions, has been developed. The results obtained using the proposed model's dynamic server load uncertainty and environmental influences show that data processing time is reduced by 15–25% compared to classical approaches. Adaptive network resource allocation under challenging conditions demonstrates the effectiveness of the proposed method.

2. The performance of a heterogeneous server network for a corporate management system in a complex smart city infrastructure environment has been assessed using a fuzzy numerical optimization method. It has been established that the problem of server load distribution under uncertainty is supported by the principle of fuzzy optimal control. The existence of a finite fuzzy rule base ensuring the required approximation accuracy has been proven using the Mamdani-Zadeh universal approximation theorem. The generated fuzzy rules and a defuzzification procedure are implemented to determine the server load distribution coefficient. The obtained results demonstrate that the fuzzy optimization method ensures server load balancing, thereby increasing the stability and reliability of a heterogeneous server network under uncertainty.

3. Based on the uncertainty principle, a fuzzy descriptive model of server operating parameters with linguistic variables has been developed, which facilitates the organization of expert knowledge and the decision-making process. A structured model of a fuzzy rule base for classifying fuzzy output parameters, organizing rules, and checking stability conditions has been proposed. It has been shown that the resulting rule base not only functions as a heuristic model but also reflects a qualitative analogue of the gradient optimization method based on multi-criteria conditions of optimal corporate governance. This approach ensures balanced load distribution, taking into account both destabilizing and stabilizing factors, thereby increasing the efficiency, reliability, and stability of the corporate network.

4. Issues related to improving the reliability of a heterogeneous server in a smart city computer network environment with a complex infrastructure and eliminating possible system failures have been addressed. An approach based on defuzzification has been used to determine the coefficient of effective network load distribution. The resulting index is set to approximately 0.68, reflecting the fact that 68% of the request flow is stored on the server, while the remaining 32% is distributed across other nodes. This result suggests that this prevents server overload. To normalize the data flow on a heterogeneous server, an algorithm for fuzzy clustering, local optimization, and automatic generation of fuzzy rules has been developed. Simulations show that the proposed fuzzy approach reduces average processing time by 15%, increases fault tolerance from 75% to 87%, and, unlike traditional methods, improves the effectiveness of corporate governance under uncertainty.

5. The advantages of fuzzy optimization and logical modeling for effective resource management under uncertainty in a heterogeneous smart city server network have been substantiated. Based on the obtained expert knowledge, a simulation has been conducted, which revealed that with a ±20% change in input parameters, the network system throughput fluctuates within 95–105 requests/sec, the response time is maintained within 190–210 ms, and the reliability is at the level of 95–99%. The proposed model is shown to ensure high fault tolerance, resilience to uncertainty, and efficient resource allocation, and has practical implications for a smart city network with heterogeneous servers.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

AI use declaration

We hereby declare that artificial intelligence tools were used solely in accordance with the journal's requirements. The AI model and the OpenAI ChatGPT version were used only for:

– preliminary development of methodological approaches;
– identifying viable models;
– initial proposal;
– further testing by the authors during the study.

The abstract, introduction, literature review, discussion of results, and conclusion sections were written by the authors themselves.

AI was also used for grammar editing: checking grammar, spelling, and punctuation without changing the text.

AI was used to search for sources for the literature review: searching for sources using keywords and criteria entered by the authors, such as only open access sources or sources from the last 5 years.

The above AI capabilities meet the requirements of the journal. All conclusions were based solely on the original work of the authors.

Authors' contributions

Javanshir Mammadov: Conceptualization, Methodology, Formal analysis, Writing – original draft; **Esmira Mekhbaliyeva**: Software, Investigation, Validation, Data curation, Visualization.

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