Fuzzy Cluster Analysis-Based Methodology for Software and Hardware Selection in Cloud Infrastructure with Unified Information Space

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Keywords: choice optimisation, data uncertainty, resource optimisation, mathematical modelling, adaptive algorithms, performance criteria.

Received: March 23, 2025

The research established a methodological framework for assessing and choosing software and hardware configurations for cloud infrastructure within a cohesive information space, employing the fuzzy c-means clustering algorithm. The principal obstacle tackled was the complexity of decision-making among ambiguity, a common occurrence in intricate IT system planning. The methodology incorporated a multi-criteria evaluation framework, encompassing performance, cost, scalability, reliability, and security, utilising fuzzy logic to address data ambiguity and expert subjectivity. A comparative analysis was performed utilising conventional approaches including AHP, TOPSIS, and Mamdani fuzzy inference. Empirical testing was conducted utilising configuration files from five prominent cloud service providers, analysing 60 distinct setups. The methodology enhanced evaluation precision by 23% and diminished expert subjectivity by 31% relative to traditional methods. The fuzzy clustering technique discerned three ideal configurations (high-performance, balanced, and cost-effective) that enhanced computer resource utilisation by 18% and diminished cloud infrastructure setup and maintenance expenses by 22%. These findings highlight the efficacy of fuzzy cluster analysis in facilitating dependable, adaptive, and resource-efficient decision-making for the design and optimisation of cloud ecosystems.

Povzetek: Raziskava predstavi metodo na osnovi mehke logike in gručenja za bolj zanesljivo in učinkovito izbiro konfiguracij oblačne infrastrukture, ki zmanjša subjektivnost odločanja ter izboljša izrabo virov in stroškovno učinkovitost.

1 Introduction

The development of information technology and the rapid growth of data volumes are creating new challenges for organisations seeking to effectively manage their information technology resources. Cloud computing has become a primary method for solving these problems, providing access to computing resources and data from anywhere and at any time. However, the selection of the optimal set of software and hardware tools to create a cloud environment with a single information space remains a complex task. Existing methods often fail to address the complexity of the interaction of various factors and the dynamic nature of cloud environments. They also struggle to effectively integrate quantitative and qualitative evaluation criteria, accommodate input data uncertainty, and ensure adaptive resource planning in a single information space.

This problem is particularly relevant in the context of deploying information infrastructure in critical industries such as defence. The experience of the Ministry of Defence of Ukraine in creating a private cloud demonstrates the importance of choosing an integration platform that allows for efficient data exchange between distributed information systems and managing complex business processes. The private cloud enables unified and standardised service delivery, providing the necessary flexibility and cost savings for deploying information systems, fast resource allocation and reliable access to application services.

Y.A. Kirpichnikov et al. [1] substantiated the use of a data-centric approach to create a single information space for the defence forces. The authors proposed a model that can describe a set of interacting processes in a single information space and can be used to determine the requirements for information systems when building a defence information infrastructure. This approach aims to increase the speed, accuracy and quality of decision-making, which are critical for strategic decisions and the success of operations and combat operations.

The issue of optimal solutions for cloud infrastructure has been extensively explored by researchers, focusing on the integration of cloud, fog, and edge computing to create a unified information space. R. Buyya and S.N. Srirama [2] highlighted the necessity of developing new evaluation and selection methods for software and hardware that specifically address the unique challenges of distributed computing environments. They argue that such integration can enhance data processing efficiency and reduce latency by leveraging the proximity of edge devices to data sources. Similarly, S.S. Gill et al. [3] examined the impact of emerging technologies on cloud computing and stressed the importance of adaptive evaluation methods for cloud environments. Their findings suggest that adaptive methods can dynamically adjust to varying workloads and resource demands, thereby optimizing performance and resource utilization in cloud infrastructures. This integration and adaptability are crucial for achieving a seamless and efficient cloud ecosystem.

Despite significant progress in this area, existing approaches often do not address the complexity of the interaction of various factors and the dynamic nature of cloud environments. Methods that would effectively integrate quantitative and qualitative evaluation criteria, accommodate input data uncertainty, and ensure adaptive resource planning in a single information space remain underdeveloped.

Y.A. Kirpichnikov et al. [4] highlighted the critical importance of strengthening the national defence capability in the context of current challenges. The researchers emphasise the critical role of quick access to secure communication platforms for managers of various levels. These platforms should provide a wide range of functions, including instant data exchange, audio and video conferencing, email correspondence, and collaborative work on documentation. In the context of a potential military threat, the information infrastructure supporting these services must meet the highest standards of resilience, continuity and protection against cyber threats.

A. Singh et al. [5] investigated the use of machine learning methods to optimise cloud environments, proposing the integration of these methods with traditional approaches to the evaluation and selection of software and hardware.

R. Buyya et al. [6] outlined the key areas of cloud computing development, emphasising the importance of developing new methods for evaluating and optimising cloud resources. R. Buyya et al. [6] analysed an integrated approach to the management and orchestration of network slides in the context of 5G, fog computing, edge computing, and cloud environments. The authors emphasised the importance of the integration of these technologies to create a single information space and efficient resource management. They emphasise the need to develop adaptive methods for evaluating and selecting software and hardware that would consider the specifics of distributed computing environments. This study demonstrated the relevance of applying multi-criteria approaches to assessing the effectiveness of integrated systems, which is significant in creating cloud environments with a single information space.

M. Kumar et al. [7] provided a detailed analysis of resource planning methods in cloud computing. The authors analysed a wide range of techniques, including heuristic, meta-heuristic, and hybrid approaches to optimising resource allocation. They emphasised the importance of effective scheduling to ensure quality of service and optimise resource utilisation in cloud environments. This study demonstrated the critical role of hardware and software evaluation and selection methods for building efficient cloud infrastructures.

Z. Zhou et al. [8] consider the concept of edge computing as a key element for the implementation of artificial intelligence in distributed systems. The authors emphasised the importance of edge computing integration with cloud environments to create a single information space and increase data processing efficiency. They emphasised the need to develop new methods for evaluating and selecting software and hardware that address the specifics of the interaction between cloud and edge components.

A burgeoning corpus of literature investigates techniques for resource selection in cloud systems; yet, substantial gaps persist. The issues encompass the poor incorporation of ambiguous data and expert judgement, restricted adaptability to various operational contexts, and a lack of methodological rigour in measuring configuration efficiency. This work presents a methodology based on fuzzy cluster analysis to improve decision-making in the selection of cloud infrastructure, specifically within a unified information space.

This work aims to design and verify a decision-support approach for selecting software and hardware configurations that ideally satisfy performance, scalability, affordability, security, and reliability criteria in complex cloud settings. The fuzzy c-means clustering technique is pivotal to this initiative, enabling the handling of ambiguous and partial input data, supporting multi-criteria decision-making, and mitigating expert prejudice. The research examines the effectiveness of fuzzy clustering method in real-world scenarios where organizations must choose between different cloud deployment models. The methodology is evaluated through quantifiable outcomes, including increased evaluation accuracy, reduced variability in expert assessments, improved computing resource utilization, and lowered operational costs. The methodology is expected to enhance evaluation precision by over 20%, reduce expert subjectivity by over 30%, increase resource utilization by approximately 18%, and decrease infrastructure-related expenses by more than 20%. These benchmarks serve as concrete indicators of methodological success and provide a robust framework for comparison with traditional techniques like AHP, TOPSIS, and Mamdani fuzzy inference. The study contributes a systematic, scalable, and adaptable framework for evaluating and selecting cloud infrastructure configurations, integrating fuzzy logic with cluster analysis and applying it in diverse operational scenarios.

2 Materials and methods

The research methodology aimed to develop and evaluate a methodology for selecting software and hardware to create a cloud environment with a single information space. The methodological approach was based on a comprehensive analysis of existing methods for evaluating and selecting IT infrastructure components, with a particular focus on the possibilities of using fuzzy cluster analysis to improve the decision-making process in this area.

At the initial stage, a thorough theoretical analysis was conducted, which included the study of such methods as the Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Mamdani’s fuzzy inference method. AHP can be used to structure a complex task into a hierarchical model and calculate relative priorities based on expert opinions. The TOPSIS method is based on the idea of comparing alternatives by their similarity to the ideal solution. Mamdani's fuzzy inference can be used to handle linguistic variables, which is important when there is data uncertainty. This analysis was used to identify the advantages and limitations of each approach, which became the basis for the development of a new methodology based on the use of fuzzy cluster analysis.

The AHP method, developed by Thomas Saaty, can be used to structure a complex choice problem in the form of a hierarchy of criteria and alternatives. This method is effective for qualitative evaluation criteria and enables expert judgement inputs. However, the AHP method has limitations with many alternatives and does not consider the uncertainty of input data.

The TOPSIS method is based on the concept that the best alternative should have the shortest distance from the ideal solution and the longest distance from the worst. This method can efficiently rank alternatives but does not address the interdependence of criteria and data uncertainty.

Mamdani's fuzzy inference method uses fuzzy logic to model the decision-making process of experts. It can be used to work with linguistic variables and model expert knowledge. However, the difficulty lies in the formation of a complete rule base and the adjustment of membership functions.

The development of the methodology included the creation of a conceptual model of the evaluation process, which covered the stages from defining evaluation criteria to selecting optimal configurations. The key criteria influencing the choice of cloud solutions were identified: performance, cost, scalability, reliability and security. A key element of the proposed approach was the use of the c-means fuzzy clustering algorithm, which allowed to effectively group similar hardware and software configurations, considering the uncertainty of the input data. This approach was used to address different scenarios and multi-criteria evaluation of alternatives.

To validate the developed methodology, theoretical modelling of the evaluation process was carried out on the example of choosing software and hardware for creating a private cloud. The scenarios of choosing a public cloud platform for a startup and optimising a hybrid cloud infrastructure for a financial institution were additionally considered, which was used to assess the flexibility and adaptability of the proposed approach. The application of the methodology in different conditions demonstrated its ability to adapt to the specifics of each industry, which confirmed its versatility.

The effectiveness of the methodology was evaluated using a comparative analysis with traditional evaluation methods, including AHP, TOPSIS, and the Mamdani fuzzy inference method. The impact of the methodology on the key performance indicators of cloud infrastructure, such as the cost of computing resources and the utilisation rate of computing power, was emphasised. This was used to quantify the benefits of the proposed approach and its potential for optimising cloud environments.

The study analysed the limitations of the developed methodology, in particular, the dependence on the quality of input data and the need for expert adjustment. This was used to identify promising areas for further research, including integration with forecasting and optimisation methods, adaptation to the specifics of various industries, and extension to assess the economic and environmental aspects of cloud resources. The methodology has demonstrated the potential to improve decision-making efficiency in various contexts, as evidenced by its application in real business environments.

To empirically assess the suggested methodology, configuration data were gathered from five prominent international cloud providers: Amazon Web Services, Microsoft Azure, Google Cloud Platform, IBM Cloud, and Oracle Cloud. The dataset included 60 unique cloud infrastructure setups, with 12 from each provider, chosen to exemplify various performance levels, cost structures, scalability attributes, and security criteria. Evaluation metrics were response time (ms), uptime percentage, average latency (ms), and price, all standardised for comparability. The baseline for improvement comparisons was established as a composite score generated by utilising the AHP, TOPSIS, and Mamdani inference methods on the identical dataset. The 23% enhancement pertains primarily to the augmentation in classification precision – assessed by clustering validity indices (e.g., the Dunn index and silhouette score) – in comparison to the baseline. Furthermore, statistical significance testing was performed utilising paired t-tests at the 95% confidence level to validate the robustness of the observed enhancements.

3 Results

The study provided a theoretical justification of existing methods for evaluating and selecting software and hardware for creating a cloud environment with a single information space. The focus was on studying the possibilities of using fuzzy cluster analysis to improve the evaluation and decision-making process in this area, and three main methods that are widely used for evaluating and selecting IT infrastructure components were considered: the AHP method, TOPSIS and the Mamdani fuzzy inference method. Each of these methods has its advantages and limitations. The literature analysis revealed that existing approaches to the evaluation of software and hardware for cloud environments often do not account for the uncertainty of input data and the complexity of the relationships between different evaluation criteria. This can cause suboptimal decisions when choosing cloud infrastructure configurations. To overcome these limitations, the use of fuzzy logic and cluster analysis methods was proposed.

The analysis of these methods determined that the use of fuzzy cluster analysis can significantly improve the process of evaluating and selecting software and hardware for cloud environments. Fuzzy cluster analysis is efficient in handling uncertain and incomplete data, which is often encountered when describing the characteristics of cloud services. In addition, this method can be used to identify natural groups of similar configurations, which simplifies the process of choosing the optimal solution.

To implement the approach based on fuzzy cluster analysis, the use of the c-means fuzzy clustering algorithm was proposed. This algorithm can group objects in such a way that each object can belong to several clusters with different degrees of membership. This is especially relevant in the evaluation of cloud solutions, which often do not have clear boundaries between different categories of configurations.

The proposed methodology of fuzzy cluster analysis demonstrates higher accuracy compared to traditional methods, which is confirmed by a more accurate grouping of software and hardware configurations. For instance, the methodology achieved a 23% improvement in evaluation precision and a 31% reduction in expert subjectivity, as evidenced by empirical testing on 60 distinct cloud setups. The 31% reduction in expert subjectivity was derived from the improvement in inter-rater reliability using Cohen’s kappa. It can be used to distribute alternative solutions according to the degree of belonging to clusters based on linguistic variables, which is important for adjusting for the uncertainty and complexity of input data. In particular, the performance and reliability of cloud platforms are often described in fuzzy terms due to the difficulty of accurately measuring these characteristics in different operating conditions. Quantitative indicators such as a 17% increase in resource utilisation and a 22% reduction in computing resource costs further underscore the efficacy of this approach.

The documented 23% enhancement in precision was quantified by the silhouette coefficient, which increased from an average of 0.48 with baseline approaches to 0.59 with the fuzzy clustering technique. The Dunn index increased from 0.23 to 0.29. The results were statistically validated using a paired t-test, which produced $p<0.01$ for both parameters, signifying a statistically significant improvement in clustering quality. The decrease in expert subjectivity was evaluated via inter-rater agreement (Cohen’s kappa), which rose from 0.42 to 0.55, indicating enhanced consistency in configuration classification.

The theoretical analysis has demonstrated that the use of fuzzy cluster analysis to evaluate cloud hardware and software has several advantages. First, it is the uncertain data handling. The characteristics of cloud services are often described in imprecise or linguistic terms, and the fuzzy approach allows for effective modelling of such uncertainty. Secondly, it is the ability to identify natural groups of similar configurations, which simplifies the selection process. Thirdly, it reduces the dimensionality of the problem, as grouping similar alternatives reduces the number of options for detailed analysis. Fourthly, it is adaptable to different use cases, which makes it easy to adapt the evaluation model to the specific requirements of different organisations and types of cloud environments. And lastly, it incorporates interrelationships between the criteria, which identifies implicit dependencies between different characteristics of software and hardware.

One of the main achievements of the methodology is the ability to accommodate several alternative scenarios of cloud resource use. The study identified three main classes of configurations: high-performance, balanced, and economical. High-performance configurations are characterised by high-performance indicators but require significant financial investments. Balanced solutions have an optimal balance between cost and scalability, making them an attractive option for medium-sized companies. In contrast, cost-effective configurations offer lower implementation costs but lower performance, which can be beneficial for startups or small businesses (Table 1).

Table 1: Characteristics of software and hardware configurations for cloud infrastructure.

Type of configuration	**Productivity**	**Price**	**Scalability**	**Reliability**	**Security**	**N (Sample Size)**	**SD (±)**
High-performance	High	High	High	High	High	20	±0.8
Balanced	Average	Average	Average	Average	Average	20	±0.6
Cost-effective	Low	Low	Low	Low	Low	20	±0.9

Table 1 shows the characteristics of the three main configurations identified by the fuzzy cluster analysis. High-performance solutions are best suited for large companies with large budgets and high reliability and performance requirements. Balanced configurations provide an optimal balance between cost and performance, therefore suitable for most medium-sized companies. Cost-effective solutions are suitable for start-ups and small businesses looking to reduce costs, even if they affect overall performance and security.

A critical consideration that warrants further examination is the process of fuzzification of input data when applying fuzzy cluster analysis. Fuzzification is the process of converting clear numerical values into fuzzy sets, which can be used to handle uncertainty and imprecision in the input data. In the context of evaluating software and hardware for cloud environments, fuzzification can be applied to parameters such as performance, reliability, scalability, and cost.

For instance, the following linguistic variables can be defined for the parameter “productivity”: low productivity, average productivity, high productivity, and very high productivity. Each of these variables can be represented as a fuzzy set with a corresponding membership function. The most common types of membership functions are triangular, trapezoidal, and

Gaussian. The choice of a specific type of membership function depends on the specifics of the task and expert opinion.

The process of defuzzification, which is the opposite of fuzzification, is also noteworthy. Defuzzification can be used to transform the results of fuzzy inference into clear numerical values, which is necessary for specific decisions on the choice of software and hardware. There are several methods of defuzzification, among which the most common are the centre of gravity method, the average maximum method, and the method of the greatest of the maxima [9, 10]. The choice of a particular defuzzification method can significantly affect the result of the assessment, therefore it is necessary to conduct a sensitivity analysis of the results of the choice of defuzzification method. The centre of gravity (CoG) method – also known as the centroid method – was applied for defuzzification. The CoG method is widely adopted in fuzzy inference systems, particularly where a compromise solution is sought that balances the contributions of all fuzzy rules.

Another important aspect of using fuzzy cluster analysis is choosing the optimal number of clusters. This task is not trivial and often requires the use of additional methods to assess the quality of clustering. Among such methods are the Xi-Ben index, the fuzzy separation index, and the fuzzy entropy index [11, 12]. These indices can be used to determine the optimal number of clusters that provide the best separation of alternative hardware and software configurations.

The use of fuzzy cluster analysis also reduced the cost of computing resources [13]. As determined, the implementation of this methodology allowed to reduce costs due to a more accurate selection of cloud resource configurations that better met the needs of companies. This was achieved by optimising the use of computing power and reducing the risk of overloading or underloading cloud resources. In addition, the capacity utilisation rate increased, indicating more efficient use of computing resources under dynamic workloads (Table 2).

Table 2: Impact of the method on costs and resource use.

Parameter	Before methodology	After methodology	Difference (%)	N (Sample Size)	SD (±)
Expenses for computing resources	100%	78%	-22%	60	±2.5
Resource usage ration	65%	82%	+17%	60	±3.1

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Table 2 illustrates the impact of the methodology on resource savings and efficient use. Reduction of computing resource costs was possible due to a flexible approach to resource management based on the actual needs of companies, which was achieved using fuzzy cluster analysis. In addition, a 17% increase in resource utilisation helped to reduce capacity losses due to inefficient load planning, which had a positive impact on productivity.

A significant impact of fuzzy cluster analysis was determined by the assessment of the scalability and flexibility of the selected configurations. The proposed methodology adapts the selected configuration to the growth or change in computing resource requirements, which is critical for rapidly developing companies. The modelling process revealed that the clustering model can consider various scenarios of company development, providing the optimal configuration based on the projected changes in workloads. This is particularly relevant for companies planning to scale operations in the future.

One of the important results is a reduction in the subjectivity of expert assessments. The fuzzy cluster analysis method minimised the influence of the human factor on the decision-making process. This was achieved by applying a mathematically sound approach to data analysis, which helped to avoid errors due to subjective judgements. This is especially important in large projects, where even minor errors can lead to significant financial or technological losses.

The study also revealed the potential of using fuzzy cluster analysis to assess the environmental responsibility and energy efficiency of cloud platforms. The methodology demonstrated the ability to identify configurations that optimise energy use and reduce the carbon footprint of cloud data centres by aligning performance requirements with energy consumption profiles. Empirical modelling incorporated workload-based energy consumption estimates and region-specific electricity cost and emissions data to evaluate the environmental impact of different configurations. Results indicated that balanced configurations, while moderately performant, offered the most favourable energy-to-throughput ratio, leading to up to a 19% reduction in CO_2 emissions compared to traditional selection methods [14]. This capability is particularly valuable as sustainability indicators become increasingly integrated into enterprise IT strategies and environmental, social, and governance (ESG) reporting frameworks. Thus, fuzzy cluster analysis not only supports economic and operational efficiency but also contributes to environmental sustainability in cloud infrastructure planning.

The theoretical modelling of the evaluation process using fuzzy cluster analysis demonstrated that this approach can effectively group similar hardware and software configurations. As a result, three main clusters of configurations were identified: a cluster of high-performance solutions with a high level of security but relatively high cost; a cluster of balanced solutions with average performance across all criteria; and a cluster of cost-effective solutions with lower performance but good scalability. This clustering result broadens the understanding of decision-makers of the available options, allowing better focus on the most promising configurations for detailed analysis.

An important aspect of the proposed approach is the ability to adapt to different scenarios of using cloud environments. To demonstrate this capability, two more theoretical scenarios were considered: the choice of a public cloud platform for an e-commerce startup and the optimisation of a hybrid cloud infrastructure for a financial institution.

In a scenario simulating a startup's decision-making process for selecting a public cloud platform, criteria such as scalability, deployment speed, and cost-efficiency were prioritised. To model this scenario, empirical configuration datasets from AWS, Google Cloud, and Azure were used, focusing on entry-tier and mid-tier services tailored to high-growth environments. This cluster aligns with market-prevalent solutions used by early-stage companies seeking rapid market entry without significant capital outlays. The use of real configuration metrics and benchmarking ensured that the clustering process remained grounded in verifiable data, thus improving the validity and realism of the scenario.

Notably, the proposed approach based on fuzzy cluster analysis is not limited to the stage of choosing the initial configuration of the cloud environment. It can be effectively used for continuous optimisation and adaptation of the cloud infrastructure to changing business requirements.

It is also worth exploring hybrid approaches that combine fuzzy cluster analysis with other multi-criteria decision-making methods. For instance, a combination of fuzzy cluster analysis and AHP may allow for more effective consideration of the hierarchical structure of evaluation criteria when selecting software and hardware.

Such a hybrid approach may consist of the following steps: application of the AHP method to determine the weights of the evaluation criteria, use of fuzzy cluster analysis to group alternative configurations, and application of the AHP method to rank the resulting clusters [15]. This approach combines the advantages of both methods: the ability of AHP to accommodate the hierarchical structure of the criteria and the ability of fuzzy cluster analysis to work with uncertain data.

The theoretical analysis also demonstrated that the use of fuzzy cluster analysis can significantly improve the process of planning the development of the cloud environment. This is achieved through the ability to model various development scenarios and assess their impact on key infrastructure characteristics.

One of the important aspects identified in the study is the potential of the proposed approach to optimise the energy consumption of cloud data centres. The use of fuzzy cluster analysis facilitated the identification of configurations that balance performance with energy efficiency. This is essential not only from an economic point of view but also in the context of reducing the environmental impact of IT infrastructure.

Another notable dimension is the use of visualisation methods for the results of fuzzy cluster analysis. Visualisation demonstrates the structure of the obtained clusters and the relationships between different hardware and software configurations in greater detail. Visualisation methods include multidimensional scaling, principal component projection methods, and t-SNE [16]. These methods can be used to present clustering results in the form of two-dimensional or three-dimensional visualisations, which greatly facilitates the interpretation of results and decision-making.

Another important aspect of using fuzzy cluster analysis is to incorporate the dynamics of changes in the characteristics of the cloud environment over time [17]. Cloud technologies are evolving very rapidly, and configurations that are optimal today may become ineffective in a few months [18]. Therefore, it is necessary to develop an approach that accommodates these changes when evaluating and selecting software and hardware.

One of the possible approaches is to apply dynamic fuzzy cluster analysis, which accommodates changes in the characteristics of clustering objects over time. This approach can include collecting historical data on changes in the characteristics of software and hardware, building models for predicting changes in characteristics and applying fuzzy cluster analysis to the predicted values of the characteristics. This approach can be used to assess the current state of software and hardware as well as predict their effectiveness in the future.

Another relevant aspect is to incorporate uncertainty and risk into the evaluation of software and hardware. Cloud technologies, despite their reliability, are still associated with certain risks, such as data breaches, downtime, or unexpected changes in the pricing policy of providers [19]. Therefore, it is necessary to develop an approach that addresses these risks in the selection of optimal configurations.

The study also revealed the potential of applying the proposed approach to solve business continuity and disaster recovery problems. Theoretical modelling has demonstrated that fuzzy cluster analysis can effectively evaluate various configurations in terms of their resilience to disruption and ability to recover quickly from critical situations.

An important result of the study is the identification of the synergistic effect of combining the proposed approach based on fuzzy cluster analysis with other advanced IT infrastructure management methodologies, in particular DevOps and Infrastructure as Code. Theoretical analysis demonstrated that such a combination allows achieving a tighter integration of planning, deployment and management of cloud resources, which in turn increases the overall efficiency of the cloud environment.

The analysis of the possibilities of applying the proposed approach in the context of ensuring compliance with regulatory requirements and security standards deserves special attention. Theoretical modelling has shown that fuzzy cluster analysis can effectively address the complex relationships between various aspects of security and regulatory compliance when evaluating cloud environment configurations.

One possible approach is to apply fuzzy set theory to risk modelling. Each risk can be represented as a fuzzy set with a corresponding membership function. This incorporates not only the probability of a risk occurring but also the degree of its impact on the efficiency of the cloud environment.

For instance, the following linguistic variables can be defined for the risk of a data breach: low risk, medium risk, high risk. Each of these variables can be represented as a fuzzy set with a corresponding membership function. Consideration of these risks in fuzzy cluster analysis yields a more realistic assessment of the effectiveness of different hardware and software configurations.

A key feature of fuzzy cluster analysis is its ability to capture interdependencies between different characteristics of software and hardware [20]. For instance, increased performance often requires increased power consumption, while increased reliability may require additional redundancy costs. These interdependencies can be incorporated by using fuzzy cognitive maps (FCMs).

FCM is an oriented graph with vertices corresponding to concepts (in our case, the characteristics of software and hardware) and arcs corresponding to the cause-and-effect relationships between them [21]. The weight of each arc can be represented as a fuzzy number, which allows to consider the uncertainty in the strength of influence of one concept on another. The use of FCM in combination with fuzzy cluster analysis provides a more comprehensive assessment of the effectiveness of various hardware and software configurations, based on the complex relationships between their characteristics [22].

A noteworthy contribution of the study lies in the demonstrated impact of the proposed approach on the processes of digital transformation of enterprises. Theoretical analysis demonstrated that the use of fuzzy cluster analysis to evaluate and select software and hardware can significantly accelerate the introduction of new digital technologies and services. This is achieved by more accurately determining the optimal configurations that meet both the current and future needs of the organisation.

A significant feature of fuzzy cluster analysis is its adaptability to the specifics of different industries. Different industries have unique peculiarities and requirements for cloud environments. For example, security and regulatory compliance are critical for the financial sector, scalability and speed are critical for e-commerce, and high-performance and parallel computing are critical for scientific computing [23].

Adaptation of the methodology may include the identification of industry-specific assessment criteria, development of industry scales for assessing various characteristics, consideration of industry standards and regulatory requirements, and development of industry scenarios for the use of cloud resources. Such adaptation yields more relevant results for the evaluation and selection of software and hardware for a particular industry.

The study also revealed the potential of the proposed approach for solving problems of optimising resource utilisation in multi-cloud environments. Theoretical modelling has shown that fuzzy cluster analysis allows to effectively evaluate different options for load balancing between different cloud platforms, accounting for factors such as cost, performance and specific features of each platform.

An important result of the study is the development of a conceptual model of the process of evaluation and selection of software and hardware based on fuzzy cluster analysis. This model includes the following key stages: determination of evaluation criteria and their weighting coefficients, collection and preliminary processing of data on alternative configurations, phasing of input data, fuzzy clustering of alternatives, analysis and interpretation of clustering results, ranking of clusters and selection of optimal configurations.

It is also necessary to address the possibility of machine learning methods to improve the results of fuzzy cluster analysis. Deep learning methods can be used to automatically determine the optimal parameters of membership functions and fuzzy inference rules. For instance, neural networks can be trained on historical data on the effectiveness of various hardware and software configurations to predict the optimal parameters of fuzzy cluster analysis. This facilitates the automation of the methodology setup process and increases its adaptability to changes in cloud technology characteristics.

An important aspect of the application of fuzzy cluster analysis is also the incorporation of environmental factors in the evaluation of software and hardware. Given the growing importance of sustainability and reducing the carbon footprint, it is necessary to include environmental criteria in the evaluation process. Such criteria may include energy efficiency of equipment, use of renewable energy sources, cooling efficiency of data centres, and equipment disposal and recycling options. Incorporating these criteria into a fuzzy cluster analysis provides a more comprehensive assessment of the effectiveness of different hardware and software configurations, considering not only technical and economic aspects but also the environmental component.

Another central element involves the development of a methodology for evaluating and selection of software and hardware for edge computing. Edge computing is becoming increasingly important in the context of the Internet of Things and real-time data processing [24]. Evaluation of edge computing hardware and software has its peculiarities, such as power consumption limitations, low latency requirements, and reliability in complex environments. Adaptation of the fuzzy cluster analysis methodology to evaluate such systems may include the development of specific evaluation criteria, consideration of limitations of edge devices, and development of use cases for various edge computing applications.

The theoretical analysis demonstrated that the proposed model can effectively accommodate the uncertainty of input data and the complexity of the relationships between different evaluation criteria, which provides a more accurate and reliable decision-making process when selecting optimal hardware and software configurations for cloud environments. This is achieved using fuzzy logic, which can be applied to linguistic variables and fuzzy sets that better reflect the real nature of the parameters being evaluated. In addition, cluster analysis can reveal hidden patterns and group similar configurations, which simplifies the selection process and makes it more reasonable. Thus, the proposed model not

only improves the quality of the assessment but also provides greater flexibility and adaptability to changing conditions and requirements of modern cloud technologies.
In general, the results of the study confirm the high efficiency of the fuzzy cluster analysis methodology in the process of selecting software and hardware for cloud environments. The methodology improved the accuracy of decision-making by 23% compared to traditional methods such as AHP, TOPSIS, and Mamdani fuzzy inference. It also identified three optimal configurations: high-performance, balanced, and cost-effective, that enhanced computer resource utilisation by 18% and reduced cloud infrastructure setup and maintenance expenses by 22%. Additionally, the methodology reduced the subjectivity of expert assessments by 31%, demonstrating its effectiveness in dynamic environments where resource requirements are constantly changing. This ensures the flexibility and adaptability of cloud infrastructures, making the methodology particularly beneficial for industries with high reliability and security requirements, such as defence and the financial sector.

4 Discussion

The developed methodology for the evaluation and selection of software and hardware for a cloud environment with a single information space based on fuzzy cluster analysis demonstrates significant potential for improving the efficiency of the process of planning and deployment of cloud infrastructures. The proposed approach, based on fuzzy logic and cluster analysis, increased the accuracy of evaluating cloud infrastructure options by 23% compared to traditional methods. This is especially relevant in the face of uncertainty that often accompanies the process of selecting software and hardware for cloud environments. Additionally, three optimal configurations of tools were identified that used computing resources 18% more efficiently, which confirms the practical value of the developed methodology for real business tasks.
In comparison to the AHP, TOPSIS, and Mamdani fuzzy inference, the fuzzy cluster analysis methodology exhibits enhanced performance across multiple fundamental criteria. The fuzzy clustering method enhanced configuration evaluation precision by 23% due to its capacity to manage imprecise and linguistic input. In terms of flexibility, unlike AHP and TOPSIS, which depend on static evaluation hierarchies and are sensitive to the quantity of possibilities, fuzzy cluster analysis dynamically organises configurations and adjusts to varying input parameters and cloud settings. The methodology offers inherent categorisation of possibilities and facilitates display of cluster membership, a feature sometimes absent in Mamdani-based systems due to the complexity of their rule bases. Ultimately, fuzzy cluster analysis diminishes computing expenses by obviating laborious pairwise comparisons (as seen in AHP) or comprehensive rule-set adjustments (as in Mamdani), so enhancing scalability for extensive configuration spaces. The comparative advantages highlight the need of employing fuzzy cluster analysis in the design of cloud systems amid multi-criteria uncertainty.
The further development of cloud technologies requires the adoption of the latest trends, such as the security of Internet of Things (IoT) systems and edge computing. Y. Zhao et al. [25] emphasise the need to integrate blockchain to improve security in distributed architectures, which is an important aspect of cloud infrastructures, especially in critical applications such as defence. The integration of these aspects into the developed methodology can be used to evaluate software and hardware based on their ability to support complex architectures with high-security requirements.
The use of fuzzy cluster analysis to evaluate hardware and software also minimised the influence of subjective expert judgement, reducing this influence by 31%. This correlates with the general trend towards automating decision-making processes through machine learning and artificial intelligence, which are increasingly being used to optimise cloud environments. A. Tufail et al. [26] emphasised the importance of new network technologies integration, such as 5G and edge computing, which creates additional opportunities for adapting the developed methodology to the current conditions of information technology development. Consideration of these aspects will ensure the effective deployment of cloud services in high-speed, low-latency environments, which will improve performance and reliability.
Similar ideas were reflected by J. Wang et al. [27] and M.B. Gracia et al. [28], who analysed the prospects of using blockchain and smart contracts to ensure reliable communications in future 6G networks. This opens new horizons for improving the methodology by including criteria for assessing the security and reliability of communications, which is critical for the deployment of next-generation cloud environments. The expansion of the methodology for evaluating and selecting software and hardware in the context of edge computing, in IoT environments, creates prospects for the development of more adaptive and secure systems. J. Mendez et al. [29] emphasise the importance of integrating artificial intelligence into edge computing to improve the efficiency of IoT systems. The use of such approaches will provide a higher level of automation and security, which is especially important for critical systems such as defence and medical platforms.
The developed methodology also demonstrates the potential for further improvement by incorporating economic and environmental criteria into the evaluation process. This approach ensures a more comprehensive assessment of software and hardware that meets the current requirements of sustainable development. Q.-V. Pham et al. [30] emphasised the importance of energy efficiency and carbon footprint reduction for modern IT systems, and the inclusion of these aspects in the evaluation process will improve the ability of companies to adapt to global energy consumption challenges. A separate area for further development is the expansion of the methodology for evaluating hybrid cloud environments that include edge and fog computing. The studies by S. Deng et al. [31], A.N. Toosi et al. [32] and S.

Tuli et al. [33] emphasised the importance of integrating artificial intelligence and edge computing to improve the efficiency of resource management in such environments. Incorporation of these aspects into the methodology will expand its application to dynamic hybrid systems that combine cloud and edge computing, providing flexibility and adaptability.

The study by N.C. Luong et al. [34] on the application of deep reinforcement learning in communications and network technologies opens prospects for further improvement of the developed methodology. The integration of reinforcement learning methods can create more adaptive systems for evaluating and selecting software and hardware that can automatically optimise their parameters based on experience and feedback from the actual operation of cloud environments. J. Park et al. [35] emphasised the importance of machine learning methods for the optimisation of wireless networks in the context of edge computing. This indicates the need to expand the developed methodology to consider the specifics of wireless technologies and mobile edge computing when evaluating and selecting software and hardware for creating integrated cloud-edge environments. M. Mozaffari et al. [36] analysed the use of unmanned aerial vehicles in wireless networks. The incorporation of these aspects in the developed methodology will allow for a more efficient assessment of software and hardware in terms of their readiness for integration with mobile aerial platforms to expand network coverage and increase flexibility.

The study by W.Y.B. Lim et al. [37] on federated learning in mobile edge computing networks introduces a complementary technological domain that can enhance the fuzzy cluster analysis methodology. By integrating federated learning principles, the methodology can be extended to develop more private and efficient evaluation methods. This approach allows for the distributed analysis of software and hardware performance without the need for centralised collection of sensitive data, which is particularly relevant for organisations with stringent privacy and data protection requirements. This integration can improve the adaptability and security of cloud environments, aligning with the core objectives of optimising cloud infrastructure through advanced data analysis techniques.

The study by F. Wang et al. [38] on the application of deep learning in edge computing can be integrated to improve the evaluation process. The inclusion of criteria related to the ability of software and hardware to effectively support deep learning models on edge devices will allow the methodology to better assess the potential for creating intelligent distributed systems. This is especially relevant for scenarios where local data processing with minimal latency is required.

M. Satyanarayanan et al. [39] highlighted the importance of developing applications optimised for edge computing. This concept can be used to extend the methodology, including the assessment of software and hardware compatibility with edge-native applications. This can be used to create more efficient cloud-edge environments optimised for the specific requirements of edge computing.

The study by Q. Lin [40] on dynamic resource allocation in the edge-cloud continuum emphasised the importance of adaptive resource management. The developed methodology can be improved to assess the ability of software and hardware to support dynamic optimisation of load balancing between cloud and edge resources. This will allow the creation of more flexible and efficient cloud environments that can adapt to changing user requirements and network conditions.

J. Singh et al. [41] provided a comprehensive analysis of fog computing that can be used to expand the range of evaluated characteristics in the methodology. The inclusion of criteria specific to fog computing, such as latency, mobility, and geographical distribution of resources, will allow the methodology to better evaluate software and hardware for creating integrated cloud-fog-edge environments. K.B. Letaief et al. [42] analysed the prospects of artificial intelligence applications at the network edge in the context of future 6G networks. This concept can be used to expand the evaluation criteria in the developed methodology, including the ability of software and hardware to effectively support advanced artificial intelligence (AI) operations in high-speed, low-latency networks. W. Saad et al. [43] considered a wide range of applications and technologies expected in 6G networks. Coverage of these aspects in the developed methodology will allow for a more comprehensive assessment of software and hardware in terms of their readiness to support such technologies as holographic communications, haptic Internet, and augmented reality.

P. Porambage et al. [44] examined the relationship between security and artificial intelligence in the context of edge computing. Consideration of these aspects in the developed methodology will allow a more comprehensive assessment of software and hardware in terms of their ability to ensure the security of AI operations at the edge of the network. The importance of federated learning in the context of unmanned aerial vehicles for air quality monitoring was discussed by Y. Liu et al. [45]. Integration of these concepts into the developed methodology will allow a better assessment of the ability of software and hardware to support complex IoT scenarios with mobile, autonomous devices.

The methodology for evaluating and selecting software and hardware for creating a cloud environment with a single information space based on fuzzy cluster analysis has significant potential for improving the efficiency of planning and optimizing cloud infrastructures. It provides a substantial toolkit for solving complex selection problems under conditions of uncertainty and multicriteria typical of the modern cloud technology landscape [46]. However, to fully implement this potential, further research and development are required to overcome identified limitations and expand its scope. This includes improving automatic adaptation algorithms, expanding the set of analysed data, integrating with forecasting and optimization systems, and adapting to the specific requirements of different industries and types of organizations.

The application of the developed methodology in the context of artificial intelligence and machine learning technologies is crucial for the efficiency and scalability of AI systems. The integration of the methodology with AutoML and MLOps tools can create more efficient and automated processes for the development and implementation of AI solutions. The methodology should also be analyzed in the context of security and regulatory compliance, as the choice of software and hardware should address not only functional and economic aspects but also security and compliance aspects.

The integration of the methodology with DevOps and GitOps concepts is another promising area of development. Automation of Infrastructure as Code deployment and management processes is becoming increasingly necessary to ensure the flexibility and efficiency of IT operations. Adapting the methodology for these new paradigms can create new opportunities to optimize resource utilization and increase the efficiency of application development and deployment.

In conclusion, the developed methodology for evaluating and selecting software and hardware for creating a cloud environment with a single information space based on fuzzy cluster analysis has significant potential for solving complex optimization and decision-making problems in the field of cloud technologies.

5 Conclusions

This study validates the effectiveness of a fuzzy cluster analysis-based approach for the selection and assessment of software and hardware configurations in cloud systems with integrated information spaces. The suggested framework surpasses conventional multi-criteria decision-making tools in precision, adaptability, and diminished subjectivity. Empirical validation utilising setups from prominent cloud providers revealed a 23% increase in evaluation accuracy, an 18% enhancement in resource utilisation, and a 22% reduction in operational costs.

The method's ability to manage uncertain and interconnected evaluation criteria renders it especially advantageous for intricate and dynamic environments, such as defence, finance, and nascent edge-cloud infrastructures. The discovery of three ideal configuration clusters – high-performance, balanced, and cost-effective – demonstrates its practical relevance across many operational contexts.

The methodology's dependence on expert-defined parameters and data quality, while promising, has possible limits. Subsequent study should investigate the incorporation of predictive analytics, AutoML pipelines, and compliance modules to improve scalability, automation, and regulatory conformity. Moreover, broadening the framework to incorporate sustainability measures, like energy efficiency and carbon footprint, would synchronise it with contemporary global concerns in IT infrastructure management.

The suggested methodology provides a scalable, adaptable, and evidence-based decision-support tool for optimising cloud infrastructure. The ongoing progress offers significant potential for advancing digital transformation across industries via intelligent resource allocation and sustainable system design.

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