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Statement of the Problem of Determining the Technical Appearance and Design Characteristics of Multi-Apartment Residential Buildings Based on the Expert Systems Method

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The authors declare that there is no conflict of interest.

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Abstract. The article discusses various methods for creating decision support systems to determine the technical appearance and design characteristics of multi-apartment residential buildings at the pre-construction stage. To solve this problem, structural optimization is used, which includes determining the number of elevators, the height of the building and the number of floors, orienting the building to the cardinal directions, determining the parameters of engineering communications and the investment attractiveness of new housing. The advantages and disadvantages of machine learning methods and various types of logical inference in expert systems for determining the technical appearance and design characteristics of multi-apartment residential buildings are analyzed. A comparative analysis of the various approaches has led to the conclusion that the tools of expert systems based on fuzzy logic are the most advisable. This paper presents an overview of the fundamental principles underlying the operation of fuzzy expert systems. It also offers a critical assessment of their potential for universal applicability and versatility in addressing design challenges related to construction projects.

Keywords: decision support systems, expert systems, structural optimization, machine learning methods, technical appearance, engineering concept, fuzzy logic

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Постановка задачи определения технического облика и конструктивных характеристик многоквартирных жилых зданий на основе метода экспертных систем

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Заявление о конфликте интересов
Авторы заявляют об отсутствии конфликта интересов.

Вклад авторов
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Аннотация. Рассмотрены различные методы создания систем поддержки принятия решений для определения технического облика и конструктивных характеристик многоквартирных жилых зданий на этапе подготовки к строительству. Для решения этой задачи используется структурная оптимизация, которая включает в себя определение количества лифтов, высоты здания и количества этажей, ориентацию здания по сторонам света, определение параметров инженерных коммуникаций и инвестиционной привлекательности нового жилья. Проанализированы преимущества и недостатки методов машинного обучения и различных типов логического вывода в экспертных системах для определения технического облика и конструктивных характеристик многоквартирных жилых зданий. На основе сравнительного анализа различных подходов сделан вывод о целесообразности использования инструментов экспертных систем, основанных на нечеткой логике. Показаны основные принципы работы нечетких экспертных систем и сделан вывод об их универсальности и перспективности в задачах проектирования строительных объектов.

Ключевые слова: системы поддержки принятия решений, экспертные системы, структурная оптимизация, методы машинного обучения, технический облик, инженерная концепция, нечеткая логика

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Introduction

The technical appearance of an apartment building is determined during the design stage, which represents its conceptual engineering model. This model describes the tasks, structure, and main design characteristics of a multiapartment residential building. The model must consider the main elements that determine the compliance of a construction project with the set goals and objectives. The problem of determining the technical appearance of an apartment building is solved using structural and parametric optimization [1].

Structural optimization of the technical appearance of an apartment building involves determining the composition and interrelation of the elements of the designed construction project, and parametric optimization involves choosing the values of its parameters [2]. In relation to the problem being solved, structural optimization includes the determination of the following characteristics:

- Number of elevators in an apartment building;
- Building height (number of floors) of an apartment building;
- Orientation of an apartment building according to cardinal directions;
- Determination of engineering communication parameters;
- Determination of the investment attractiveness of a building (important for construction planning).

The technical appearance of an apartment building and its design characteristics should be determined by considering the restrictions imposed on the construction site (cost, parameters of the construction site, etc.), as well as available resources (financial, material, technical, etc.).

The purpose of this study is to determine ways to solve the problem of parametric optimization of the technical appearance and design characteristics of multi-apartment residential buildings and to justify the choice of the solutions obtained.

1. Analysis of experience in solving design problems in the field of construction using intelligent systems

The analysis and optimization of the technical appearance of an apartment building are usually carried out using various methods, including mathematical modeling, system analysis, simulation, and optimization. Currently, machine learning methods are extensively used to solve design problems in the field of construction. For example, in [3], where three-dimensional models of buildings were built using a deep learning neural network (Figure 1).

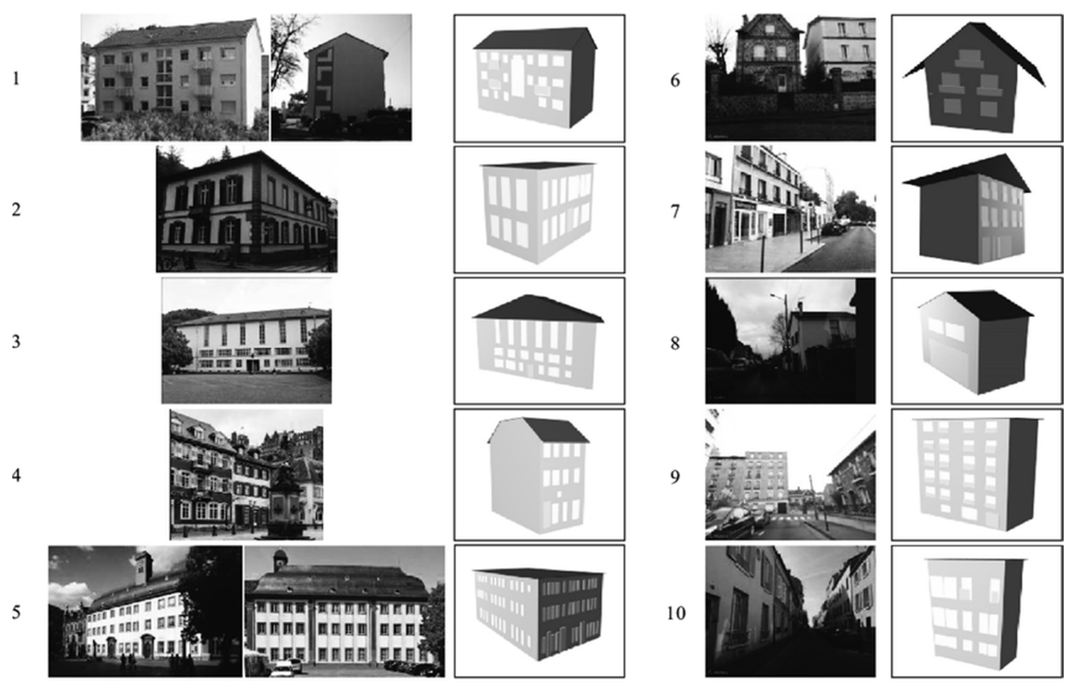

Figure 1. Three-dimensional models of residential buildings obtained using a deep learning neural network
S o u r c e: made by H. Fan et al. [3]

The open-source project* combines parametric modeling tools, data preprocessing scripts, and deep neural network models and provides the technical ability to differentiate the generalized unlabeled 3D geometry of a building in the form of informative three-dimensional models consisting of highly detailed architectural components (roofs, windows, facades, walls, chimneys, etc.). This tool allows automatic segmentation and detailed 3D building models to be segmented more efficiently and quickly than the traditional and manual software tools. An example of how the system works to detail a building model in an entire city is shown in Figure 2.

Simultaneously, the use of machine-learning methods, including neural networks, requires a large training sample.

It should be noted that there are artificial intelligence systems based on expert decisions (expert systems) rather than statistics (such as machine learning). Their essence is to use expert knowledge instead of statistical data. A comparative analysis of the neural network and expert systems for determining the physical forms and design characteristics of multiapartment residential buildings is presented in Table 1.

Figure 2. Coverage map:
a — the scale of the Montreal city model; *b* — an example of a neural network reconstruction of one city fragment
S o u r c e: Figure is taken from 3D Building Classification & Segmentation Pipeline.
Available from: https://github.com/michaelhasey/3D-Building-Segmentation (accessed: 07.01.2024).

Table 1

Comparative analysis of the neural network method and logical inference rules for the design of decision support systems in construction problems

Attribute	Neural network approach	Expert systems
Advantages	• Neural networks are capable of learning from large amounts of data and automatically extracting patterns. • Neural networks can solve problems of classification, regression, generation, and natural language processing. • The ability to adapt to changing data and conditions without the need to directly specify rules.	• The inference rules of an expert system are easy to interpret and explain. This makes them suitable for problems where it is necessary to understand how the system makes decisions. • Expert systems built on rules have predictable behavior, and changes to the knowledge base can be made through a knowledge filling block.
Restrictions	• Neural networks can be difficult to interpret and their decisions can sometimes appear to be a “black box”, making their decision making less transparent. • Training neural networks requires a massive amount of data, and in some areas the data may not be sufficient.	• Constructing rules and formalizing knowledge can be a difficult task, especially in complex scenarios. • Inference rules cannot learn from data in the same way as neural networks. They depend on the manual creation of rules by experts.
Areas of use	It is used in tasks that require analysis of large amounts of data, pattern recognition, natural language processing, and in tasks where patterns are difficult to formalize with rules.	It is effective in scenarios where transparency and interpretability of decisions are important, as well as in areas where knowledge is easily formalized, which is convenient for construction engineering problems.

An analysis of the literature has shown that a significant proportion of expert systems for construction problems is based on the mathematical apparatus of fuzzy logic [4–17]. Knowledge engineering methods have been used to develop expert systems.

Knowledge engineering is a field of artificial intelligence that studies the application of methods for organizing, collecting, analyzing, representing, storing, and using knowledge in expert systems [18]. It includes methods of acquiring, structuring, storing, retrieving, retrieving, and applying knowledge.

A knowledge engineer (cognitologist) plays a significant role in creating an expert system. The task of a knowledge engineer is to acquire and formalize knowledge in one or another formalism (logical, production, frame, and other models of knowledge representation) with the subsequent setting of a task for programmers. To solve this problem, it is advisable to use logical-inference systems.

A comparative analysis of crisp and fuzzy logic in the design of expert systems for construction is presented in Table 2.

Table 2

Comparative analysis of crisp and fuzzy logic in the design of expert systems in construction

Attribute	Crisp logic	Fuzzy logic
Basic principles	Works with precise, discrete values and rules. All knowledge and rules are expressed using strictly defined conditions and actions.	Allows you to work with fuzzy values, as well as fuzzy rules. Provides tools for describing uncertainty and fuzziness in data.
Application in expert systems	• In expert systems based on clear logic, rules and knowledge are formulated in an explicit, logical form. An expert system is capable of making decisions when knowledge and input data exactly match specified conditions. • Expert systems built on the basis of clear logic work well in tasks where rules and knowledge are strictly defined. They are easy to develop and provide accurate results.	• In expert systems based on fuzzy logic, rules and knowledge can be expressed in natural language. An expert system based on fuzzy logic is capable of making decisions even if the data is fuzzy or inaccurate. • Fuzzy logic expert systems can handle complex scenarios where data is fuzzy and are suitable for problems where expert knowledge can be expressed using linguistic variables and fuzzy inference rules.
Advantages and Limitations	Simple to consider and implement, but it is not always possible to take into account the uncertainty and fuzziness of the data. It works when tasks and rules are clear and strictly followed.	Allows to take into account and handle fuzziness, which makes it useful in real-world situations where data is often imprecise. However, it may require more complex knowledge engineering.

Determining the input and output parameters serves as the initial stage in the formation of the knowledge base underlying an expert system. These data were structured, systematized, and adapted for use by the logical core of the expert system. Text documents and standards contain a significant amount of information that should become part of the knowledge base, providing the expert system with a set of key factors for analyzing input information and making decisions.

To formalize expert knowledge, the mathematical apparatus of fuzzy logic was chosen based on the analysis in Table 2. This apparatus is more flexible than traditional (crisp) logic and allows the construction of multidimensional response surface functions, which resemble hypersurfaces reproduced by neural networks during the learning process on the training set. Mamdani's algorithm allows us to reconstruct a response surface function that projects the hypersurface into a space consisting of n dimensions, where n represents the number of factors that influence the phenomena under study. This approach allows for a more complete and accurate representation of the relationships and dependencies between various variables in a fuzzy system. This analysis is the basis for making recommendations aimed at improving the system efficiency. In particular, this is important for determining defuzzification methods, the shapes of membership function curves, and other parameters. The response surface allows customization of the operation of the system and increases its accuracy and predictive ability.

Systems based on fuzzy logic operate with linguistic variables, each of which has its own specified membership functions. In the context of fuzzy logic, a variable may not only be classified as belonging or not belonging to a specific set, but it may also be assigned a degree of membership according to the membership function associated with that set. For example, a variable temperature of +10 °C may belong to the set "warm" with a membership of 65% and the set cold with a membership of 20%. An example of this function is shown in Figure 3.

Thus, fuzzy logic makes it possible to take into account and model uncertainty, fuzziness and variability in the parameters, which seems to be a significant aspect in the construction industry. The use of fuzzy logic in expert systems allows flexible modeling of various scenarios, which helps to increase the efficiency and accuracy of decisions.

The Mamdani inference system uses membership functions to express fuzzy rules and logical connections between inputs and outputs in accordance with the diagram shown in Figure 4.

This algorithm for a conditional expert system consisting of three rules is shown in more detail in Figure 5.

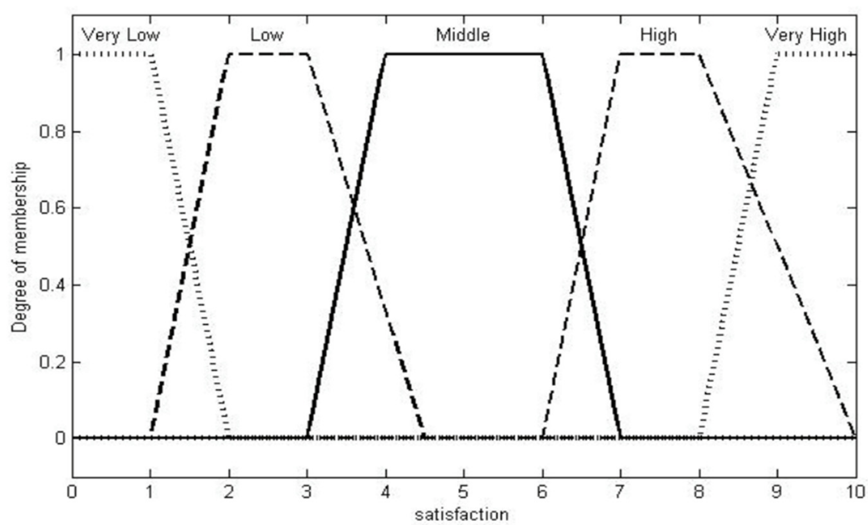

Figure 3. Fuzzy membership function of the satisfaction evaluation variable. The abscissa axis shows the score in points, the ordinate axis shows the level of membership in the range of possible values from 0 to 1 S
So u r c e: figure was taken by I. Iancu [19]

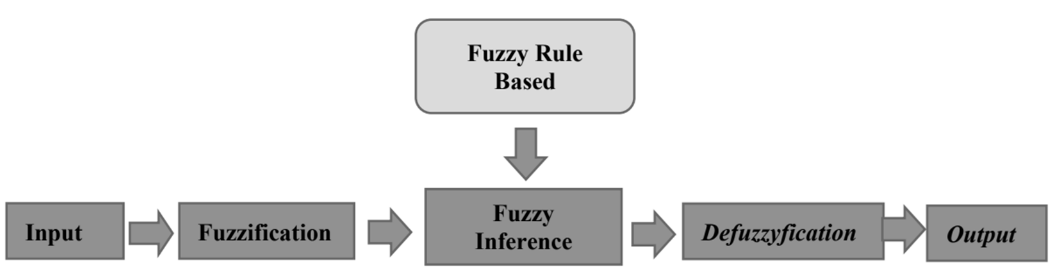

Figure 4. Schematic diagram of expert systems with fuzzy logic
So u r c e: figure was taken by A.M. Abadi [20]

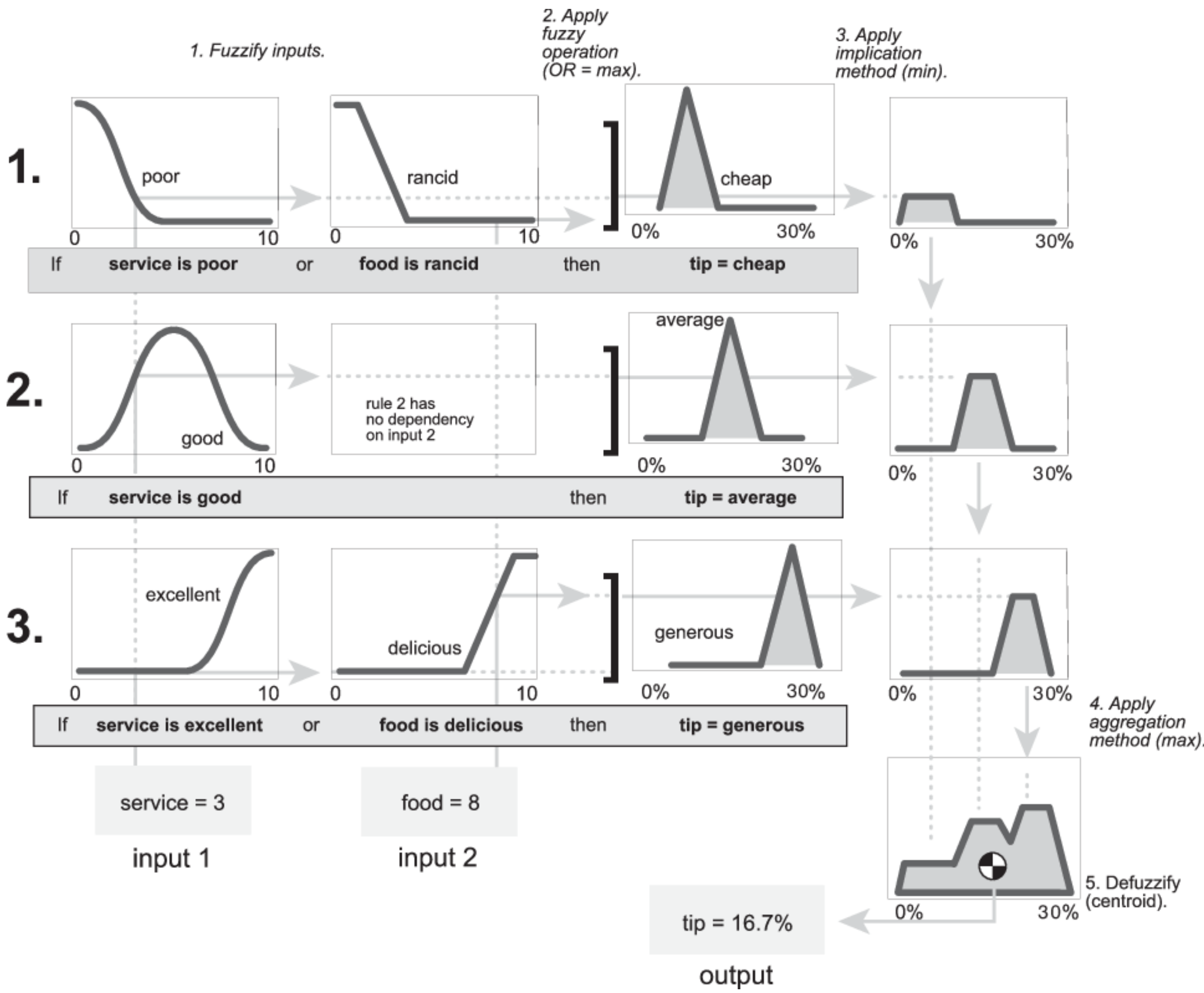

Figure 5. Mamdani algorithm
So u r c e: figure is taken from Mathworks. Help Center. Mamdani and Sugeno Fuzzy Inference Systems. Available from: https://www.mathworks.com/help/fuzzy/types-of-fuzzy-inference-systems.html (accessed: 07.01.2024).

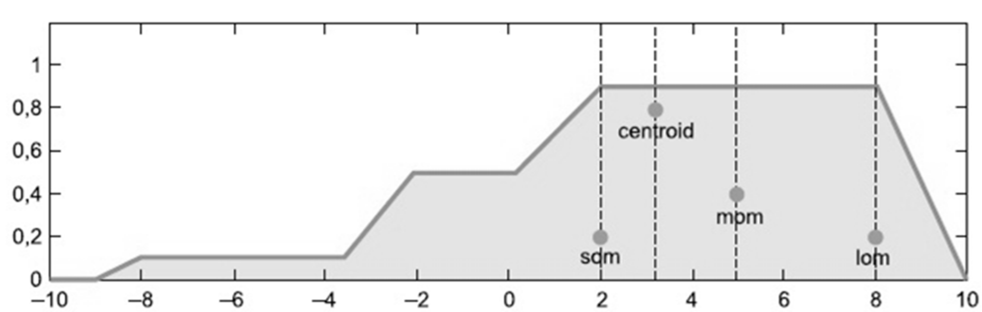

Figure 6. Illustration of methods of defuzzification: sdm, centroid, mom, lom
S o u r c e: figure is taken from Mathworks. Help Center. Mamdani and Sugeno Fuzzy Inference Systems. Available from: https://www.mathworks.com/help/fuzzy/types-of-fuzzy-inference-systems.html (accessed: 07.01.2024).

The final step of this algorithm is to reduce the clarity (defuzzification) of the fuzzy output values. This process is schematically shown in Figure 6.

The Mamdani algorithm has a high degree of rule interpretability. Owing to the use of fuzzy sets and rules that constitute the knowledge base, this algorithm has some degree of resistance to noise in the data, similar to neural networks. Mamdani's algorithm includes the following steps:

• *Fuzzification. The process of transforming input variables from numeric values into fuzzy sets using membership functions. Each input variable is associated with a fuzzy set that describes the degree to which it belongs to each term (category).*

• *Definition of fuzzy rules based on linguistic variables and terms that have been defined in fuzzification. The rules describe the logical relationships between the input and output variables in terms of "if-then" in a fuzzy form.*

• *Rule aggregation. By combining the output values of the fuzzy rules for each variable, union operations are used to obtain a common fuzzy output.*

• *Defuzzification converts the fuzzy inference result back into numeric values based on the membership function.*

• *In the last stage, the system makes a decision based on the numerical values obtained after defuzzification (control signal or recommendation).*

Any expert system specializes in a narrow problem area and is based on a knowledge base built based on the interaction of a knowledge engineer with sources of information, including experts [18].

In the design and construction of buildings, where fuzzy and weakly formalized rules operate, fuzzy logic provides flexibility in describing the conditions and relationships between variables. This is useful in situations where precise numerical values may be difficult to determine, or where there is a significant degree of uncertainty. The knowledge base of an expert system based on the Mamdani algorithm includes rules, facts, procedures, and logic specific to solving problems associated with specialized aspects of construction and is a repository of information that covers key aspects and expert knowledge in the field of construction. The generalizing properties of a knowledge base allow us to analyze and solve problems efficiently and accurately, thereby providing recommendations and solutions to the end user.

Main types of defuzzification:

• *Center of Gravity (COG, Centroid):* the weighted average of all elements belonging to the fuzzy set.

• *Maximum Method (Max-Min Method):* the element with the highest degree of membership in the fuzzy set is selected.

• *Weighted Average Method:* Each element belonging to a fuzzy set is weighted according to its degree of membership; subsequently, these weighted values are averaged.

• *Quasi-average Method (Modified Center of Sums, MCS)*: a weighted average of all elements, with the weight of each element defined as the sum of the degrees of membership of all elements that are greater than or equal to that element.

• *Averaging the Maximum of Maximums (AMOM):* The average values of the elements with the maximum membership degree at each iteration are calculated. The defuzzified value is the result of the last iteration.

• *LOM (Largest of Maxima):* the element with the highest degree of membership in the set is selected.

• *SOM (Smallest of Maxima):* the element with the smallest degree of membership in the set is selected.

• *Bisector:* an element that divides a fuzzy set into two equal parts (the defuzzified value is exactly in the middle of the set).

2. Statement of the problem of parametric optimization of the technical appearance and design characteristics of multi-apartment residential buildings using the method of expert assessments

A comprehensive study of literature and open-source information allows one to explore the theoretical foundations and standards in the construction industry, as well as familiarize oneself with current research and best practices, which is very important for the formation of basic knowledge and understanding of what is already known in the field.

To enrich the system with more practical and expert methods, it is also important to interact with subject matter experts in the construction industry. Experts can gain valuable practical knowledge and experience that can be incorporated into the system to accurately and realistically simulate the situations encountered in the field.

Thus, the combined approach of collecting knowledge from literature sources and interacting with professional experts provides a comprehensive and reliable knowledge base for creating a prototype expert system for problems in the construction field. As a rule, the process of developing an expert system begins with communication between a knowledge engineer and experts in order to adopt their experience, knowledge, and decision-making methods. A knowledge engineer identifies the key aspects, rules, and contexts that experts use to solve problems in their field. The knowledge engineer then transforms this knowledge into the form of rules that can be perceived and used by the expert system. The initial stage of expert system development establishes a fundamental framework that facilitates subsequent advancements, encompassing the capacity to accommodate novel data and revisions to building standards. Filling the knowledge base with logical inference rules plays a decisive role in the successful implementation of an expert system since the accuracy and completeness of the knowledge base directly affects the system's ability to adequately analyze data and make informed decisions. The rule-filling module provides a mechanism for systematizing, structuring, and entering acquired knowledge into the expert system. Objects, their attributes, and relationships are defined in accordance with the accepted knowledge engineering methods used for the design and creation of expert systems [18]. Once a model is developed, it must be tested on the test data to evaluate its accuracy and efficiency.

As a result of this research, a primary prototype of an expert system was created in the form of a software platform with a user interface. In accordance with the developed architecture, the expert system consisted of separate specialized modules. Each module performs its own tasks and is designed based on expert knowledge. It should be noted that when developing an expert system, the number of knowledge bases may not coincide with the number of calculation modules that use these bases.

Conclusion

The research presented in this paper represents the development of a methodology for automated engineering decision support systems in the construction industry based on the theory of expert systems and the theory of fuzzy sets. The use of the logical inference apparatus in the architecture of an expert system allows one to navigate engineering problems associated with design and construction and represents a new, innovative approach to solving engineering problems.

The automation of decision support processes in the design of building placement on a construction site is an important component of the construction industry. This approach helps improve housing infrastructure based on expert knowledge and increases investor appeal and the overall quality of construction projects. Automation of decision-making in the design process allows you to take into account various parameters, ranging from the orientation of the building to the cardinal directions and ending with engineering requirements. An approach to automating decision support for multi-apartment residential construction problems has the potential to speed up construction processes, increase the level of safety, ensure the sustainability of structures, and ultimately improve the overall quality performance of construction projects.

Based on the calculated numerical values, it is possible to build a 3D model of the house on the construction site. It is also possible to add information regarding nearby gas pipelines, parking lots, trees, and other information to determine the required setbacks from the site boundaries.

The implementation of the proposed methodology opens up new prospects for the use of expert systems for the design of housing facilities and stimulates further research in the field of development of intelligent information systems to determine the technical appearance and design characteristics of multi-apartment residential buildings. Overall, decision-support automation in design and construction contributes to the development of the construction industry.

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