DOI: https://doi.org/10.14256/JCE.4027.2024
Građevinar 9/2024

Primljen / Received: 24.4.2024.
Ispravljen / Corrected: 29.8.2024.
Prihvaćen / Accepted: 3.9.2024.
Dostupno online / Available online: 10.10.2024.

Application of expert systems in civil engineering

Authors:

Ena Grčić, MCE
J. J. Strossmayer University in Osijek
Faculty of Civil Engineering and Architecture Osijek
egrcic@gfos.hr
Corresponding author

Prof. **Marija Šperac**, PhD. CE
J. J. Strossmayer University in Osijek
Faculty of Civil Engineering and Architecture Osijek
msperac@gfos.hr

Subject review

Ena Grčić, Marija Šperac

Application of expert systems in civil engineering

Expert systems represent “IF-THEN” algorithms that integrate human expert knowledge to solve complex problems. This area of research focuses on finding solutions to challenging situations that are often difficult to resolve using traditional methods. Expert systems have widespread applications in the field of construction. The paper presents some of these applications, including their use in building maintenance, inspection of water and sewage systems, geotechnical engineering, road maintenance, and the selection of appropriate construction materials. Artificial neural networks are effective in optimizing financial plans, estimating the duration of activities, assessing the productivity of work teams, and selecting contractors. Genetic algorithms find their application in resource allocation, selecting optimal solutions for task scheduling and project costs, as well as in building maintenance, while fuzzy logic aids in risk analysis, project management, and cost estimation. Expert methods can be integrated into information systems to provide consistent information necessary for the effective management of construction projects. A review of published papers on the application of expert methods in construction shows that these methods are already significantly represented across all sectors of the construction industry, but also indicates that there are still substantial opportunities for their future application.

Key words:
civil engineering, expert systems, artificial neural networks, genetic algorithms, fuzzy logic

Pregledni rad

Ena Grčić, Marija Šperac

Primjena ekspertnih sustava u građevinarstvu

Ekspertni sustavi predstavljaju “IF-THEN” algoritme koji integriraju ljudsko ekspertno znanje radi rješavanja kompleksnih problema. Ovo područje istraživanja fokusira se na pronalaženje rješenja za izazovne situacije koje su često teško rješive klasičnim metodama. Ekspertni sustavi imaju veliku primjenu u građevinarstvu. U radu su prikazane neke od primjena: primjena kod održavanja građevina, inspekcije vodovodnih i kanalizacijskih sustava, primjena u geotehničkom inženjerstvu, održavanje prometnica te odabir odgovarajućih građevnih materijala. Umjetne neuronske mreže efikasne su kod optimizacije financijskog plana, procjene trajanja aktivnosti, procjene produktivnosti radne ekipe te izbora izvođača radova. Genetski algoritmi nalaze svoju primjenu u alokaciji resursa, odabiru optimalnih rješenja kod rasporeda zadataka i troškova projekata te održavanju građevina, dok fuzzy logika pomaže u analizi rizika, upravljanju projektima i procjeni troškova. Ekspertne metode mogu se integrirati u informacijske sustave kako bi pružile dosljedne informacije potrebne za učinkovito upravljanje građevinskim projektima. Pregled objavljenih radova o primjeni ekspertnih metoda u građevinarstvu pokazuje da su ove metode već značajno zastupljene u svim sektorima građevinarstva, ali također upućuje na to da postoje još velike mogućnosti za njihovu buduću primjenu.

Ključne riječi:
građevinarstvo, ekspertni sustavi, umjetne neuronske mreže, genetski algoritmi, fuzzy logika

1. Introduction

Construction is a complex sector that faces numerous daily challenges and problems during all project phases [1]. Large construction companies are increasingly investing in the implementation of expert methods to more easily and quickly gain a competitive advantage in the labour market [2, 3]. Considering the economic importance of the construction sector, low labour productivity during construction processes represents a significant problem. This problem results in the inefficient use of manpower, material resources, and financial resources [4]. Construction activities play a key role in the economy; therefore, it is important to focus on improving the management of construction processes to increase productivity and improve the overall efficiency of products [5]. In this context, the construction sector is undergoing constant innovation towards digitisation to achieve significant progress in automation, productivity, and reliability. With the goal of launching real digital strategies in construction engineering, expert methods serve as the foundation for transforming construction projects. Although there has been a significant increase in the amount of engineering data in construction projects, the adoption of expert methods still lags behind that in other industries [4]. Therefore, there is significant interest in implementing different expert methods in the field of construction to take advantage of the valuable opportunities of digital evolution to achieve improved efficiency and profitability.

Expert systems were introduced in various industries during the 1970s and 1980s that became important tools for solving specific problems. The first commercially successful expert system, XCON, was developed at Carnegie Mellon University to assist the Digital Equipment Company (DEC) in configuring their VAX computer systems [6]. The development of expert systems has accelerated, and many companies have started their own projects. For example, DuPont developed 100 expert systems in 1988, achieving significant operational savings [7]. These systems have quickly become essential in various industries, including construction, as they provide sophisticated tools for solving complex engineering problems and optimising processes.

This paper provides an overview of the application of expert systems in the maintenance of buildings, inspection of sewage and water systems, geotechnical engineering, roadways, and the selection of suitable building materials. The research analysis emphasises that the use of neural networks enables fast and precise data processing, which results in the efficient forecasting of future costs and a reduction in the risk of financial discrepancies. This study presents the application of neural networks in the construction industry, focusing on their ability to accurately predict costs, activity duration, labour productivity, and the selection of construction contractors. Furthermore, the various applications of fuzzy logic in construction are highlighted, from modelling work risks at the construction site to identifying the causes of project delays to predicting the final costs of projects. At the end of the paper, the application of genetic algorithms in resource allocation, project planning, the selection of optimal solutions, and building maintenance is investigated.

2. Methodology

Figure 1 illustrates the methodology used in this study. Google Scholar, which contains the most published academic and scientific literature, was used for the literature search. During the process of selecting appropriate keywords, the term "decision support systems for construction optimization" was first searched using Google Scholar. Subsequently, several scientific papers were selected from 2015 to 2024 to further identify and expand keywords and research directions, and to enable detailed research of current methods in the field. From the final list of keywords, 204 relevant papers were identified. After a thorough review of the selected papers, an additional selection was made, whereby 102 papers were selected for a more detailed analysis and review that were most in line with the objectives, including 87 scientific articles, seven conference papers, and eight book chapters.

Figure 2 shows the distribution of the number of works used according to the period in which they were published. Of the works that were used, 80 % were published in the period from 2011 to 2024.

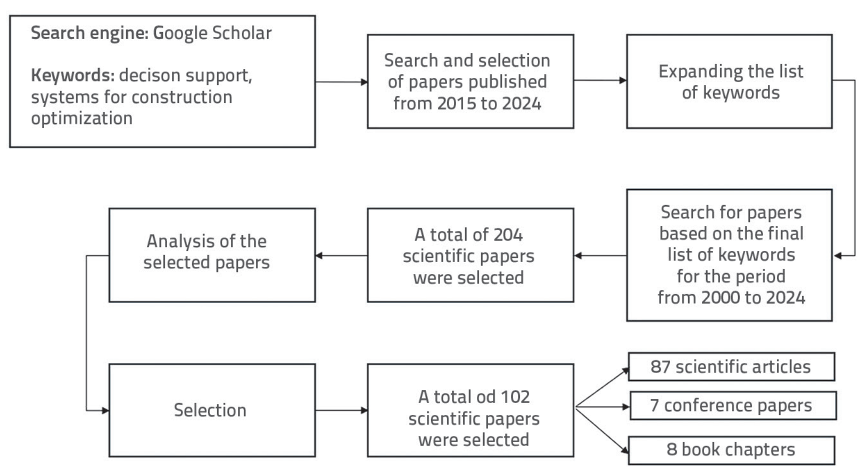

Figure 1. Research methodology

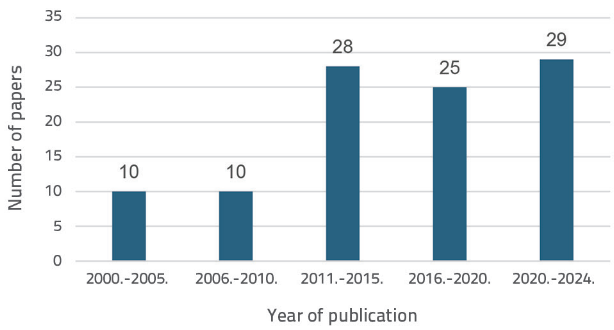

Figure 2. Presentation of the number of papers used in this study according to the time periods in which they were published

3. Basic characteristics of expert systems

Expert systems focus on finding solutions for challenging situations that are often difficult to solve using classical methods [8]. Over the past 50 years, computer science researchers have made significant strides in developing expert systems to consider real-world dynamic problems that require fast and precise answers and are often challenging for traditional problem-solving approaches [5]. The most common structure of expert systems is rule-based systems, also known as production systems. This type of system uses knowledge that is formulated through production rules, using "IF-THEN" logic [9].

Figure 3 shows how the different components of the knowledge-processing system are integrated. A knowledge base containing rules (e.g. IF-THEN) and a database containing facts are connected to the inference engine. An inference engine uses rules and facts to make inferences. This information is sent to the user through a user interface. There is also a link between the explanation and inference engines, indicating that the system can explain how the conclusions were reached. Finally, the user interacts with the system through a user interface. The arrows in the diagram show the flow of information or the direction of interaction among these components.

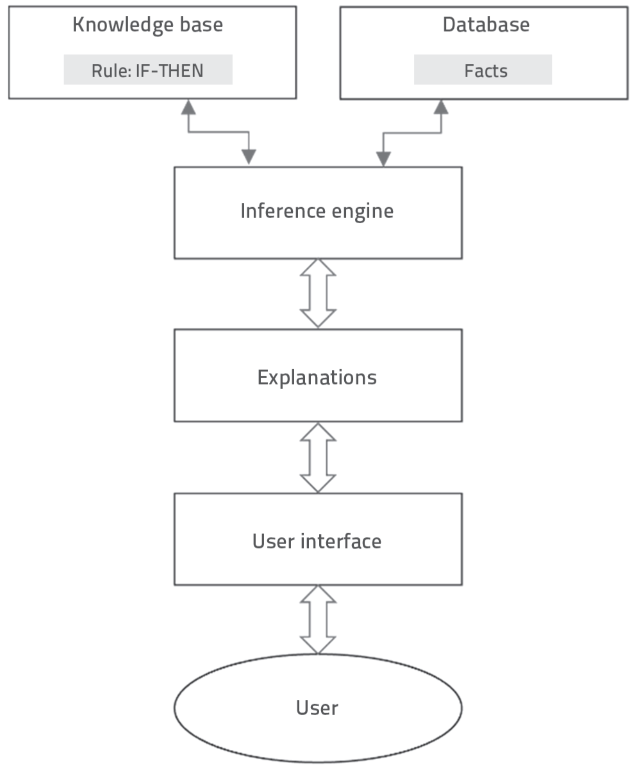

Figure 3. Components of an expert system[9]

Table 1 lists the advantages and disadvantages of expert systems. Owing to the possibility of self-programming, expert systems allow users to build systems without the need for programmers, thereby enabling faster and more efficient application development. The ability to apply rules to large sets of information ensures reliability, consistency, and transparency. Expert systems are scalable, quick to update, capable of dealing with little knowledge, and can provide answers in complex situations. However, expert systems have significant drawbacks. They are designed to solve a specific range of problems, which makes them unsuitable for more general scenarios. However, the high costs of development, implementation, and maintenance contribute to their limited

Table 1. Advantages and disadvantages of expert systems [9]

Advantages of expert systems	Disadvantages of expert systems
Quick availability and the possibility of self-programming	They cover only a narrow spectrum
Scalability	High price
Reliability and consistency	Lack of intuitive reasoning
Ability to utilize a considerable amount of knowledge	Inability to adapt to changing environments
Robustness and efficiency	They depend on symbolic input
Transparency	Errors in the knowledge base

applicability. Expert systems often lack intuitive reasoning, and may contain errors in their knowledge bases, resulting in incorrect choices. Furthermore, because of their fixed knowledge base, they find it difficult to adapt to changing situations without continuous updates. They rely on symbolic inputs, which limits their ability to understand ambiguous or incomplete data.

4. Overview of the application of expert systems in construction

In the modern construction sector, where projects are increasingly complex and require a high level of precision, expert systems are becoming indispensable tools for process management and optimisation. The application of expert systems in construction can cover various aspects, from design and planning to construction and maintenance [10]. These systems can be used for resource scheduling optimisation, project cost forecasting, risk analysis, infrastructure maintenance, and many other applications. Their ability to provide fast, accurate, and efficient solutions often surpasses that of traditional methods, thereby contributing to the progress and efficiency of the construction industry [11]. Further in this study, the application of expert systems in the areas of building maintenance, sewage and water supply systems, geotechnical engineering, roads, and material selection is analysed.

During the maintenance phase, building maintenance teams often spend considerable time gathering information from various electronic and hard-copy documents. The activities of searching, sorting, checking, and recreating information are constantly repeated [12]. Minimising the impact of problems requires seamless electronic data exchange such that building maintenance teams have a comprehensive and accurate database [13]. Expert systems can significantly improve and accelerate facility maintenance.

A subcategory researched in this area is information integration using different techniques such as relational databases and real-time data [14, 15], data warehouses [16], cloud technology [17], web services based on the use of agents [18], the ontology of the semantic web [19], and the application of data mining techniques for the extraction of useful information from building information modelling (BIM) to support activities during the maintenance phase [20].

Other studies focused on the integration of different technological platforms. For example, information extraction based on the interaction of building information modelling and geographic information systems (GIS) [21, 22], integration of 2D barcodes and mobile devices [23], and integration of BIM with radio-frequency identification (RFID) [24, 25].

BIM and GIS are similar in that they model spatial information [26, 27]. To enable interaction between BIM and GIS, compatibility is required, which can be achieved through a suitable platform [28]. Mignard and Nicolle [29, 30] presented the concept of maintaining urban infrastructure facilities. The ACTIVe3D platform was used to integrate data from the BIM and GIS systems. Through the concept of maintaining urban infrastructure facilities, the integration of BIM and GIS through the ACTIVe3D platform enables the modelling of all relevant information about the city, including geographic elements. Kang and Hong [31] proposed a BG-ETL platform for the efficient integration of data from BIM and GIS. The data were arranged according to information and geometry. To enable the visualisation of numerous objects displayed through a geographic information system, the model was adapted using geometric data from industry foundation classes, and the information on properties was extracted and transformed. Research results [27-32] show that such expert systems provide a clearer perception of the relationships between elements, reduce memory load, and improve system performance, which are crucial for large projects that contain a large amount of data, better connection of data from different sources, and provision of semantic queries for customised 3D views, thus enabling precise analysis.

Research [33-36] describes a computer system that integrates building model elements using BIM and RFID to improve building maintenance performance. Radio frequency tags are attached to the elements of the building, and each tag contains certain information about the elements obtained from the BIM database. Staff can record information, such as conditions, descriptions of problems encountered during maintenance, inspection results, recommendations, and dates. Research [33-36] shows that with minimal effort in the implementation of the proposed system, a significant improvement in the building maintenance process can be achieved compared with traditional methods, which is reflected in time, cost savings, and improved functionality [34,35]. Kameli et al. [34], based on the conducted research, claim that the reduction of total costs by more than 50 % was achieved during the maintenance process.

Lin et al. [37] presented a building maintenance process that included a two-dimensional (2D) barcode and BIM system. The system provides a platform for sharing building maintenance information. Within the framework of the study, the traditional method was compared with the proposed system, and the results of the conducted research clearly showed that the time required for basic building maintenance activities using BIM and 2D barcode systems was significantly reduced.

To maintain the functionality and stability of urban infrastructure systems, inspection of sewage systems is unavoidable. It is important to regularly monitor and maintain the network of drains through which large amounts of wastewater pass, with the aim of avoiding possible unwanted consequences such as leaks, blockages, or even environmental disasters. Experts have used various techniques to assess the condition and functionality of sewage systems, identify potential problems, and implement appropriate measures to ensure long-term efficiency.

Hahn et al. [38] created an expert system to determine the priorities for inspecting drainage systems. This system assesses potential risks and consequences, suggests appropriate inspection methods, and warns users when additional information is required to make more precise decisions.
The SCRAPS expert system was previously developed [39]. Four public institutions jointly developed a set of analyses of drainage systems and gathered three case studies based on their experiences. Their analyses focused on risk identification and failure mechanisms. Experts assessed risks with different degrees of probability, and criticality was determined using weighted factors. Based on this, sewage systems are categorised according to their risks. This process tested the accuracy of SCRAPS software and enabled experts to better plan the maintenance and management of drainage systems, improve efficiency, and reduce the risk of failure. Giovanelli and Maglionicio [40] used SCRAPS to predict critical segments of a sewer network. Data on the pipe diameter, flood frequency, root penetration, sediment accumulation, corrosion, pipe age, groundwater level, pipe depth, and other relevant parameters were entered into the SCRAPS database. It has been proven that the combination of SCRAPS and hydraulic modelling can be extremely useful for assessing sewer system data and planning the necessary inspections to maintain a constant level of system functionality.
pour la Gestion, L'Entretein et L'Exploitation du Reseaux d'Assainissement (APOGEE) analysis method and optimised programming for the management, maintenance, and exploitation of wastewater treatment networks. They developed this system to optimise the annual planning and renovation of the sewage network. This system, which consists of an expert system, database, and module for planning interventions and repairs, contributes to the construction industry by improving maintenance efficiency, reducing costs, and extending infrastructure life.
Tagherouit et al. [42] developed an expert system that helps in the renovation of sewer pipes by suggesting priority in the renovation of sewer pipes. A property index was calculated for each network segment. During the calculation, three key properties were considered: hydraulic, structural, and global. Using the property index, information is obtained regarding the condition of the sewer pipes, environment in which the sewer pipe is located, and hydraulic characteristics of the pipe. An accurate classification provides advantages in deciding which sewer pipes need to be renovated. The advantage of this evaluation system is not only in the inclusion of various parameters but also in the investigation of how they interact with each other.
Managing water supply systems is challenging because operators must react quickly to changes in demand and maintain stable conditions. While many decisions are made based on experience and intuition, mathematical models help optimise the system by considering various parameters such as water consumption, pressure, water quality, and energy efficiency [43].
Leon et al. [44] presented the EXPLORE expert system in their work. This system was developed to help manage water-supply networks. Its main objectives are to analyse daily water demand and adjust flow to ensure sufficient water without unnecessary loss or overconsumption, monitor and adjust water flow in tanks, maintain an optimal level considering daily demand, and optimise the use of pumps to reduce electricity costs, which contributes to the sustainability of the system. Their study indicated a significant reduction in electricity costs, achieving savings of 25 % [44].
Moglia et al. [45] developed a water pipe inspection prioritisation system (PARMS-PRIORITY) to help make decisions regarding pipe repairs and renovations. The system comprises five modules: risk calculation, failure prediction, cost estimation, scenario evaluation, and data exploration. Risk was calculated as a combination of the probability of failure and the associated costs. The main advantage of the PARMS-PRIORITY system is that it displays failure and cost forecasts for individual pipes or the entire system, allowing users to determine which pipes should be rebuilt first. It is integrated with a GIS system that makes it easy to quickly locate problem areas and provides detailed information about pipes such as their diameter, length, and soil type.
Fares et al. [46] presented an expert system for assessing the risk of water-pipe bursting. This expert system consists of four key categories: physical factors, operational factors, environmental impact, and consequences, each of which includes risk factors that affect the probability of water-pipe bursting. The proposed expert system enables engineers to analyse and evaluate each segment of a water pipe in detail, providing concrete risk information and recommendations for priorities in water pipe maintenance.
Sandeep and Rakesh [47] developed a system that uses simulations to generate knowledge for solving various real-time water maintenance situations. It integrates hydraulic modelling with expert knowledge using a unique CLIPS platform. In addition, it integrates computing platforms, such as MATLAB, GIS, and RDBMS, under a simple user interface. The results show that the proposed system is capable of advanced modelling, calibration, and simulation of water supply systems, providing a dynamic approach for the management of water supply networks.
Karasneh and Moqbel [48] developed a decision-making system to prioritise the restoration of water pipes. Based on the opinions of 23 experts, five main categories dominating the decision-making process were identified: physical, environmental, operational, sociocultural, and service quality. The developed system was tested on five water networks requiring renovation in Amman, Jordan. The test results indicated that the system successfully provided a clear list of priorities for the restoration of water networks.
Expert systems have significant applications in geotechnical engineering. This section provides an overview of their

applications in various aspects of geotechnical engineering, such as slope stability analysis, analysis of factors that cause landslides, landslide location, selection of the most effective method for the rehabilitation of collapsed slopes, and prediction of dry soil density.

Ana and Bauwens [41] highlighted the application of the Analyzes et Programmation Optimise

Physical models are often applied to analyse slope stability to prevent potentially catastrophic consequences of sliding. However, the application of such models can be time consuming, and because of their two-dimensional nature, they usually have to be repeated for each segment being investigated [49, 50]. In a previous study [51], a combined hydrology and stability model (CHASM) was implemented using GIS. Users can select a variety of input data, including information on precipitation, soil characteristics, infiltration, and topography. This expert system enables a quick analysis of slope stability without the need for detailed data preparation. The simulation results were automatically stored in a database and could be visually displayed for easier interpretation.

Muthu and Petrou [52] presented an expert system that identified factors that promote landslides. The first part of the system includes permanent factors, such as geological characteristics, landslide history, and other permanent conditions at a particular location. Based on these factors, the system assessed the potential severity of landslides. Another part of the system focused on changing factors such as precipitation and changes in land use. These changing factors were used to create a scoring system that identified the factors promoting landslides.

In [53], an expert system for assessing the occurrence of landslides using data from Satellite Pour l'Observation de la Terre (SPOT) images. Based on these recordings, the system builds a database containing information on landslide locations, characteristics (size and shape), and environmental conditions. An expert system analyses these data to identify areas with a high risk of landslides and enables the quick identification of potentially dangerous areas.

In another study [54], an expert system was used to create a map showing where landslides are most likely to occur on the island of Lefkada, Greece. The database was created by analysing data obtained from field research, such as lithological units, terrain slope, slope orientation, distance from hydrographic networks, and distance from traffic networks.

Adhikari et al. [55] developed a system whose task is to recommend the most appropriate rehabilitation method for collapsed slopes. It is used to rank different rehabilitation methods based on defined criteria in the system, such as the impact on traffic, durability, and speed of execution. The importance of the selection criteria for each method is calculated using the entropy method. Based on the data collected from experts and the importance of each specified criterion, the system uses a technique for preferential ranking by the similarity of the ideal solution to choose the most effective method for the rehabilitation of the collapsed slope.

Albusoda et al. [56] used an expert system supported by MATLAB to predict the soil dry density. The following input data were used to create the system: yield strength, plasticity limit, plasticity index, moisture content, specific gravity, sieving accuracy of fine particles, total suspended particles, and organic materials. The results indicated that the predictions obtained using the expert system were very close to the actual experimental data.

Over the last few decades, expert systems have become key tools in various civil engineering disciplines, including road construction and maintenance. These systems play an important role in solving specific challenges faced by road engineers, which vary according to the conditions and circumstances in the field. Unique engineering experience is crucial for identifying these challenges and recommending optimal solutions that are often unavailable at all construction sites.

Mosa et al. [57] in their work presented an expert system in which a database was stored in the form of rules and coded in Microsoft Visual Basic, supported by a GIS compatible with Visual Basic. The developed ES-CCPRHP is a knowledge-based system for managing problems in the construction of rigid roadways. The system underwent a thorough check and was validated in three ways: detailed testing, comparison of the system results with expert assessments, and analysis through case studies. It can be used as a database for archiving problems arising during the construction of rigid pavements, sharing engineers' experience,, and transferring information to future generations of engineers.

Milad et al. [58] developed an expert system to maintain roads in tropical regions. The system is based on the knowledge and data provided by engineers whose specific areas of expertise are road maintenance and road design. The IF-THEN technique was used to make recommendations, and the system was programmed in a hypertext preprocessor (PHP). The user interface of the system was built using the hypertext markup language (HTML) and cascading style sheets (CSS).

Al-Mansour et al. [59] developed a system that helps in selecting the most appropriate road maintenance method for Saudi Arabia. The user of the system can define criteria such as the traffic level, time period of analysis, and critical value for assessing the state of a road.

Pereira et al. [60] developed an expert system for prioritising highway sections in Brazil that required repair. This research was conducted to help authorities allocate funds to 20,315 km of highway. The system ranks highway segments according to their geographic location and operational characteristics, considering socioeconomic and demographic data, transportation infrastructure, traffic, highway capacity, pavement conditions, drainage, and weather conditions. Experts participated in determining weighting factors for prioritising funds. The system is reliable and provides data to support decision making, and the methodology can be applied to other regions.

In modern construction, the implementation of expert systems for the selection of building materials plays a key role in optimising construction and maintenance processes and achieving high standards of sustainability and efficiency. Jadid and Badrah [61] implemented an expert system that focused on material approval issues, selection criteria, and material information management with the goal of improving knowledge exchange among civil engineers. The system consists of a database and decision components that rely on the value-optimisation method. The database improves the selection process by providing key information on material quality, durability, and maintenance.

Yang and Ogunkah [62] presented an expert system that aids in the selection of materials for the construction of ecologically sustainable buildings (green buildings) considering criteria such as costs, durability, environmental impacts, energy efficiency, availability, and aesthetics. This system enables the storage, management, and integration of material data using an analytical hierarchical process. The database was developed based on feedback from experts, a literature review, and feedback from construction companies, and database management was implemented using MS Excel.

Akadiri et al. [63] considered the problem of selecting sustainable building materials, i.e., materials that should have a positive impact on the environment, reduce resource consumption, minimize waste, have acceptable costs during their lifetime, and meet high standards of functionality and durability. An analytical hierarchical process was used for each of these key factors, which enabled their weighted numerical evaluation. Based on this numerical evaluation, the system can make concrete recommendations regarding which material is the best choice in the context of a specified project or task.

4.1. Artificial neural networks

Artificial neural networks are modelled after biological neural networks. Similar to biological neural networks, an artificial neural network consists of nodes connected in a neuron-like manner [64]. Each neural network has three key components: node characteristics, network topology, and learning rules [65]. An artificial neural network acquires knowledge through learning. There are two basic ways of learning: supervised and unsupervised. Different neural networks use different learning strategies, depending on the tasks they need to solve [66].

Figure 4 shows the architecture of an artificial neural network. The nodes in neural networks are organised into layers, of which three main types are distinguished: input, output, and hidden. The input layers of the artificial neural network represent the starting point and are used as the data input. The hidden layers are used for data processing, and the output layers represent the final processing results.

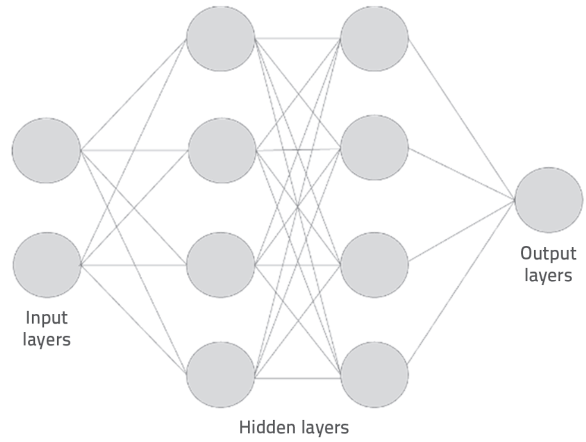

Figure 4. Architecture of an artificial neural network [67]

Effective financial management is the key to the smooth execution and timely completion of construction projects. Poor financial management can cause additional costs that create serious problems for contractors and investors, and in some cases, can lead to work stoppages owing to a lack of resources. With the help of neural networks, fast and precise data analysis is achieved, which enables efficient forecasting of future costs and reduces the risk of financial inconsistencies [68, 69].

ElSavy et al. [70] presented a neural network model using a backpropagation algorithm to predict the construction site overhead in Egypt. This study uses data from 52 real projects executed between 2002 and 2009 to train a neural network. The results showed a root mean square error value of 0.2764 and an accuracy level of 80 %. It was found that the model incorrectly predicted the site overhead percentage for only one project (20 %) using the test sample.

Moselhi and El-Sawah [71] used neural networks with a backpropagation algorithm, probabilistic neural networks, generalised regression neural networks, and regression analysis models to estimate the costs of steel structures. The research results showed that the mean absolute percentage error of the neural network model ranged from 16.83 % to 19.3 %, whereas it was 23.72 % for the regression model. The linear regression model was more sensitive to the changes in the number of training data, while the probabilistic neural network was the most stable network among all three models, with a maximum difference in mean absolute percentage error of 2.46 %.

Yadav et al. [72] developed a cost-estimation technique based on artificial neural network principles to predict the structural costs of residential buildings. The cost data from 1993 to 2016 were collected to train the network. The collected parameters included the costs of cement, sand, steel, aggregates, and skilled and unskilled workers. The parameters were simulated using NEURO XL version 2.1. The neural model predicted the total structural costs of the construction projects with a correlation coefficient (R) of 0.9960.

Pessoa et al. [73] presented a cost prediction neural network model consisting of 11 variables: building height, average height between floors, average volume, useful building area, roof area, sanitary room area, open space value, number of floors, floor construction type, roof construction type, and base plate. An analytical model based on a multi-layer perceptron that can estimate the cost of residential buildings was presented.

The introduction of artificial neural networks in construction planning provides advanced possibilities for accurate duration prediction and activity management. The application of artificial neural networks in construction includes the prediction of the duration of concrete operations and the development of tools for estimating the duration of activities, such as placing reinforcement and concreting.

Maghrebi et al. [74] used an artificial neural network to predict the duration of concrete operations, focusing on ready-mixed concrete supply chain parameters. The available database includes deliveries of ready-mixed concrete over 4 months from 17 warehouses and more than 200 trucks. The model accurately predicted the productivity of concrete operations in the range 8–15 m^3/h. However, for lower (less than 5 m^3/h) and higher productivity levels (more than 15 m^3/h), there was greater variation in the model predictions.

Golizadeh et al. [75] proposed a tool for estimating the duration of activities related to the structural elements of concrete-frame buildings. Four neural models were developed to calculate the durations of column reinforcement, beam reinforcement, column concreting, and beam concreting. The correlation coefficients (R) for the four models–column reinforcement placement, column concreting, beam concreting, and beam reinforcement placement–were 0.9863, 0.9857, 0.9803, and 0.9604, respectively, indicating the excellent predictive performance of the model.

The introduction of artificial neural networks into the analysis of labour productivity in the construction industry represents a significant step towards process optimisation. Using a neural network to predict productivity, researchers have identified and analysed multiple factors that affect labour efficiency, including worker age, experience, site conditions, weather conditions, and availability of materials and equipment.

Aswed [76] used an artificial neural network to predict worker productivity based on 30 factors. Factors such as age, experience, health of the work crew, number of workers, wages, weather conditions, availability of materials, site conditions, wall length, wall height, mortar type, wall thickness, and site safety were used as input variables. The model predicts real labour productivity with reasonable accuracy, with a correlation coefficient of R = 86.28 %. The study concluded that the model can be used to predict labour productivity in any type of construction project using the listed influencing factors.

Another previous study [77] presented a neural network model for assessing the productivity of the work team in the execution of final works. Ten key factors, including age, experience, number of support workers, floor height, wall height, cladding size, safety conditions, health status of the work team, weather conditions, site conditions, and availability of construction materials, were used as input variables. The results showed that the network can predict productivity in the execution of final work with a correlation coefficient of 87.55 % and a prediction accuracy of 90.9 %.

Choosing the right contractor for a project is crucial. To better assess the contractor's ability, neural networks have been used to analyse information from tender documents. This information includes the number of bids, compliance with conditions, and the financial stability of the contractor [78]. A multilayer perceptron has been used with the NeuroSolution tool for analysis. Multilayer perceptron refers to a specific neural network architecture used for data modelling, whereas the NeuroSolution tool is a software tool that enables the implementation of a multi-layer perceptron and performs data analysis [79].

4.2. Fuzzy logic

Fuzzy logic is a type of logic that differs from classical (bivalent) logic because it allows the existence of partial truth. Classical logic uses only two values: true and false–while fuzzy logic uses a continuous spectrum of values between zero and one to describe the truth of a statement. Sets are a basic component of fuzzy logic and represent a method of modelling uncertainty and ambiguity [80, 81]. Fuzzy logic is a powerful tool for modelling and solving problems that are not black or white. This allows us to use vague information to make decisions and draw conclusions in situations in which classical logic may be insufficient [82].

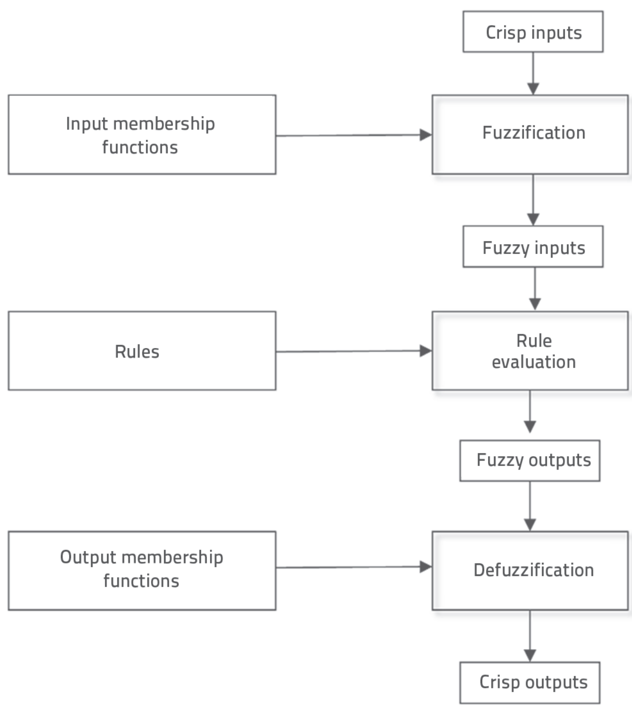

Figure 5. Steps of fuzzy logic [83]

Figure 5 illustrates the steps of the fuzzy logic. Clear inputs are specific values entered into the process. This is followed by a fuzzification process, in which clear inputs are transformed into fuzzy inputs. In the rule evaluation process, fuzzy inputs are converted into fuzzy outputs. During the defuzzification process, the fuzzy outputs are transformed into final results or clear outputs representing the response of the system.

Assessment of occupational risks is important for the safety of workers at construction sites. This process uses various parameters; however, obtaining precise information is often difficult. Traditional methods are often insufficiently accurate for determining risks and proposing preventive measures. Fuzzy logic has been used to develop a model for occupational risk assessment [84]. Using advanced inference and analysis techniques, the model provides tools that help construction companies make informed decisions and effectively manage safety risks [82].

Liu and Tsai [85] proposed a method that uses two-level tables to apply a quality function to show the relationships among a group of construction works, the type of hazard, and the cause of the hazard. A fuzzy analytical network process was applied to identify the most important types of hazards and their causes, and to assess the risk of these causes.

Janackovic et al. [86] proposed a fuzzy analytical hierarchical process for ranking the criteria used to assess the level of safety at a construction site. The basic requirements for safety at work (risk, costs, and social responsibility) were identified as criteria, factors that influence the quality of safety at work (technical, human, organizational, and external environmental factors) as sub-criteria, and key indicators of safety at work were identified as alternatives. A case study was conducted on road construction companies, and the results showed that organizational factors had the greatest influence on the quality of the occupational health and safety management system.

Seker and Zavadskas [87] presented a new approach for occupational risk assessment at construction sites that helps project managers adopt appropriate preventive strategies to avoid accidents at construction sites. The proposed fuzzy method reveals the relationships between factors and rank criteria according to the type of relationship and the intensity of their effects on each criterion.

In addition to being used for risk analysis, fuzzy logic has also been applied in the management of construction projects. Construction project delays are common and inevitable. When there is a delay in an activity, the engineer managing the project must determine the duration of the delay and how it will affect the rest of the project schedule. It often happens that even if the engineer managing the project knows that there is a problem of delaying work on a certain activity, he may not be able to accurately estimate how long the delay will last, what the consequences will be, and whether it will cause a delay in the final completion of the project. Therefore, it is useful in project management to have tools to help update the project plan based on delay analysis.

Oliveros and Fayek [88] presented a fuzzy logic model that integrated the daily site reporting of activity progress and delays with a schedule update system and construction monitoring and control. The developed model helps analyse the impact of delays on the project completion date and consists of several components: a database of the performed state integrated with the project schedule, a list of potential causes of delays, a delay categorisation procedure, a method for estimating the duration of the delay using fuzzy logic, a procedure for updating the schedule, and a procedure which assesses the impacts and likely consequences of delays on the progress of activities.

Gunduz et al. [89] presented a tool that uses fuzzy logic together with a relative importance index method to help construction contractors estimate the probability of project delay. Based on a literature review and interviews with civil engineers, 83 factors that could cause delays were identified that were divided into 9 main groups. The importance of these factors was measured using the relative index method, and the factors and groups were ranked according to the extent to which they affected the delay. The most important delay factors were analysed according to the results of this project, and the model showed satisfactory results.

Cost overruns in construction projects are a very common phenomenon that occur because of poor quality and insufficient planning. Cost overruns can have a large effect on the financial structure and timeline of a project; therefore, it is very important to conduct early analysis and cost control [90]. Karla and Aminah [91] developed a model based on fuzzy logic to calculate the extent to which the final costs of a project will be higher or lower than the contracted price. The model performs estimations based on the project characteristics. It considers factors such as the scope, complexity, and duration of the project, as well as resource requirements. Furthermore, the model considers potential risk events. Delays, lack of resources, changes in requirements, and unforeseen complications are examples of risk events.

4.3. Genetic algorithms

The best answer is typically determined from a limited number of available choices. The search space refers to the set of all conceivable options. Each point in the area represents a potential solution, which can be evaluated based on its degree of adaptability. Genetic algorithms are heuristic methods for exploring the space to determine an ideal solution, such as minimisation [92]. However, obstacles in this context often include the presence of local minima and difficulties in initiating the search. Genetic algorithms exhibit several key characteristics. First, they are stochastic algorithms, implying that they involves certain elements of randomness. Algorithm selection and replication procedures rely heavily on randomness [93]. Using the principles of natural selection, multiple solutions can be combined to obtain superior results. Robustness is another important feature of genetic algorithms. They are highly adaptable and can be used to solve various problems without requiring additional criteria [94].

Figure 6 shows the working process of a genetic algorithm that starts with a randomly generated population of solutions. The selection of the optimal solutions from the population serves as a parent to create a new generation of solutions. Thus, information is recombined to create new individuals. Subsequently, a mutation process is performed to preserve the population diversity. Each individual is evaluated according to the criteria and the optimal solution is the output of the genetic algorithm. This process is iteratively performed until the stopping criterion is satisfied.

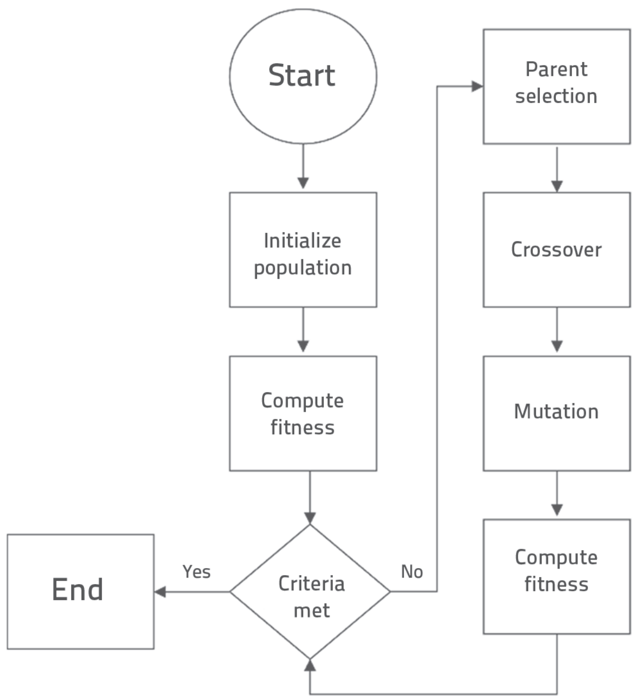

Figure 6. Genetic algorithm working process [95]

The proper allocation of resources is essential for project success and process improvement. Resource allocation and levelling are complex tasks, particularly when they must be optimized simultaneously [96]. Using a genetic algorithm to solve these problems involves five steps: defining the genetic structure, setting the criteria for gene evaluation, creating an initial population, choosing a method to generate new generations, and implementing the procedure in a computer program. Paper [97] proposes a genetic algorithm that improves existing schedules created with the help of commercial project management tools.

Genetic algorithms have found their application in various areas of optimization, including planning and project management in construction, have been applied to various areas of optimisation. Zhang et al. [98] developed a genetic algorithm to optimise task scheduling with minimal project costs by considering deterministic and stochastic task durations. Their genetic algorithm generates a schedule of tasks and issues guidelines for their execution through stochastic distribution simulations. The results show that the genetic algorithm can reduce the total cost up to 19.57 % under deterministic conditions. Also, it significantly reduced execution time by approximately 66 %. Altanany et al. [99] presented a mathematical model that used matrices to represent project activities and applied a genetic algorithm to optimise project duration and costs. The authors introduced a new mathematical approach for the optimisation of linear projects using matrices, which allows for better scheduling of activities and determination of optimal schedules. Genetic algorithms have proven to be powerful tools for automatically determining optimal architectural structures in BIM systems. Tafraour et al. [100] proposed an innovative approach based on a genetic algorithm to automatically determine the optimal structure for a certain architectural configuration in a BIM system. The methodology is based on a multicriteria optimisation process that generates an initial population of potential configurations that satisfy architectural constraints and general structural rules. The results show that the proposed approach is highly effective in generating optimal structures that meet the defined criteria and structural design requirements.

In the field of building maintenance, genetic algorithms integrated with discrete event simulations represent an advanced model for optimising maintenance plans. Nili et al. [101] presented a new model that integrated a genetic algorithm and discrete event simulation to identify an optimal bridge maintenance schedule considering manpower constraints. The framework focused on minimising agency and user costs in a bridge repair project by considering practical limiting factors such as resource and work crew limitations. Ward and Savić [102] used a genetic algorithm for drainage system maintenance. The model included minimising construction costs, maximising structural condition improvements, and minimising failure risk, and its effectiveness was tested on sewer systems in Devon, Cornwall, Dorset, and Somerset in the UK.

5. Conclusion

This paper analysed the application of expert methods in the construction sector for the period from 2000 to 2024, with special emphasis on building maintenance, inspection of sewage and water supply systems, geotechnics, traffic engineering, project cost forecasting, project duration, risk reduction on construction sites, and workforce productivity. The goals of this study were achieved through a detailed analysis of the application of expert construction methods. The research showed that expert systems, such as SCRAPS and EXPLORE, are crucial for optimising the maintenance process of facilities and infrastructure. The integration of BIM, GIS, and RFID technologies has enabled advanced data analyses, resulting in cost reduction and increased efficiency. Neural networks can successfully predict site overheads and material costs, reduce variations, and improve the productivity of work operations. Fuzzy logic enables more precise risk analysis, activity management, and better estimation of final costs. The application of genetic algorithms in project planning and integration with BIM and discrete event simulations has resulted in significant cost reduction and optimisation of maintenance plans. During our research, one of the main problems was the limited number of available papers that presented detailed and clear results of the application of expert methods in the construction sector, specifically fuzzy logic and neural networks. Although many studies have described the application of these methods to specific cases, clear information on the concrete results and contributions of these studies is often lacking. In addition, the papers that dealt with the application of genetic algorithms were somewhat more detailed, especially in recent publications (2020–2024). However, even in these studies, concrete information on how the research results contributed to a better understanding or optimisation of the process was often missing. A review of published works on the application of expert methods in construction shows that they are widely applied in all sectors of construction; however, there are also great opportunities for the application of these methods in the future. To further improve the application of expert methods in the construction sector, it is necessary to continue developing and adapting the system to specific needs and conditions; ensure adequate training and education for construction engineers who will work with these systems; and encourage cooperation among academic institutions, industrial partners, and legal bodies to ensure the adoption and application of the latest practices and standards.

REFERENCES

[1] Jin, R., Zou, Y., Gidado, K., Ashton, P., Painting, N.: Scientometric analysis of BIM-based research in construction engineering and management, Engineering, Construction and Architectural Management, 26 (2019) 8, pp. 1750-1776, https://doi.org/10.1108/ECAM-08-2018-0350.

[2] Manzoor, B., Othman, I., Durdyev, S., Ismail, S., Wahab, M.: Influence of Artificial Intelligence in Civil Engineering toward Sustainable Development - A Systematic Literature Review, Applied System Innovation, 52 (2021) 4, pp. 1-17 https://doi.org/10.3390/asi4030052.

[3] Giang, D.T.H., Sui Pheng, L.: Role of construction in economic development: Review of key concepts in the past 40 years, Habitat International, 35 (2011) 1, pp. 118-125, https://doi.org/10.1016/j.habitatint.2010.06.003

[4] Pan, Y., Zhang, L.: Roles of artificial intelligence in construction engineering and management: A critical review and future trends, Automation in Construction, 122 (2021) 103517, https://doi.org/10.1016/j.autcon.2020.103517.

[5] Walek, B., Fojtik, V.: A hybrid recommender system for recommending relevant movies using an expert system, Expert systems with applications, 158 (2020) 113452, https://doi.org/10.1016/j.eswa.2020.113452.

[6] Badiru, A.B., Cheung, J.Y.: Fundamentals of expert systems (Chapter), Fuzzy engineering expert systems with neural network applications, New York, John Wiley & Sons, pp. 13-24, 2002.

[7] Gupta, I., Nagpal, G.: AI and Expert Systems, Artificial intelligence and expert systems (Chapter), First edition, Virginia, Mercury learning and information, (2018), pp. 71-93.

[8] Tan, H.: A brief history and technical review of the expert system research, IOP Conf. Series: Materials Science and Engineering, 2017, https://doi.org/10.1088/1757-899X/242/1/012111.

[9] Guerrero, J.I., Personal, E., García, A., Parejo, A., Pérez, F., León, C.: A rule-based expert system for heterogeneous data source integration in smart grid systems, Expert Systems: Design, Applications and Technology, (2017), pp. 60-92.

[10] Santos, J., Torres-Machi, C., Morillas, S., Cerezo, V.: A fuzzy logic expert system for selecting optimal and sustainable life cycle maintenance and rehabilitation strategies for road pavements, International Journal of Pavement Engineering, 23 (2022) 17, https://doi.org/10.1080/10298436.2020.1751161.

[11] Abioye, S.O., Oyedele, L.O., Akanbi, L., Ajayi, A., Delgado, J.M.D., Bilal, M., et al.: Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges, Journal of Building Engineering, 44 (2021) 103299, https://doi.org/10.1016/j.jobe.2021.103299.

[12] Edirisinghe, R., London, K.A., Kalutara, P., Aranda-Mena, G.: Building information modelling for facility management: are we there yet?, Engineering, Construction and Architectural Management, 24 (2017) pp. 14-47, https://doi.org/10.1108/ECAM-06-2016-0139.

[13] Sabol, L.: BIM Technology for FM (Chapter), BIM for Facility Managers, John Wiley & Sons, (2013), pp. 17-45, https://doi.org/10.1002/9781119572633.ch2.

[14] Kang, T.W., Choi, H.S.: BIM-based Data Mining Method considering Data Integration and Function Extension, KSCE Journal of Civil Engineering, 22 (2018) pp. 1-12, https://doi.org/10.1007/s12205-017-0561-6.

[15] Solihin, W., Eastman, C., Lee, Y.C., Yang, D.H.: A simplified relational database schema for transformation of BIM data into a query-efficient and spatially enabled database, Automation In Construction, 84 (2017), pp. 367-383, https://doi.org/10.1016/j.autcon.2017.10.002.

[16] Ahmed, A., Ploennigs, J., Menzel, K., Cahill, B.: Multi-dimensional building performance data management for continuous commissioning, Advanced Engineering Informatics, 24 (2010) 4, pp. 466-475, https://doi.org/10.1016/j.aei.2010.06.007.

[17] Curry, E., O'Donnell, J., Corry, E., Hasan, S., Keane, M., O'Riain, S.: Linking building data in the cloud: Integrating cross-domain building data using linked data, Advanced Engineering Informatics, 27 (2013) 2 pp. 206-219, https://doi.org/10.1016/j.aei.2012.10.003.

[18] Shen, W., Hao, Q., Xue, Y.: A loosely coupled system integration approach for decision support in facility management and maintenance, Automation in Construction, 25 (2012), pp. 41-48, https://doi.org/10.1016/j.autcon.2012.04.003.

[19] Kim, K., Kim, H., Kim, W., Kim, C., Kim, J., Yu, J.: Integration of ifc objects and facility management work information using Semantic Web, Automation in Construction, 87 (2018), pp. 173-187, https://doi.org/10.1016/j.autcon.2017.12.019.

[20] Peng, Y., Lin, J.R., Zhang, J.P., Hu, Z.Z.: A hybrid data mining approach on BIM-based building operation and maintenance, Building and Environment, 126 (2017), pp. 483-495, https://doi.org/10.1016/j.buildenv.2017.09.030.

[21] Kang, T.W., Hong, C.H.: A study on software architecture for effective BIM/GIS-based facility management data integration, Automation in Construction, 54 (2015), pp. 25-38, https://doi.org/10.1016/j.autcon.2015.03.019.

[22] Mignard, C., Nicolle, C.: Merging BIM and GIS using ontologies application to urban facility management in ACTIVe3D, Computers in Industry, 65 (2014) 9, pp.1276-1290, https://doi.org/10.1016/j.compind.2014.07.008.

[23] Lin, Y.C., Su, Y.C., Chen, Y.P.: Developing Mobile BIM/2D Barcode-Based Automated Facility Management System, The Scientific World Journal, 2014 (2014) 374735, pp. 1-16, https://doi.org/10.1155/2014/374735.

[24] Motamedi, A., Saini, R., Hammad, A., Zhu, B.: Role-based access to facilities lifecycle information on RFID tags, Advanced Engineering Informatics, 25 (2011) 3, pp. 559-568, https://doi.org/10.1016/j.aei.2011.03.004.

[25] Motamedi, A., Soltani, M.M., Setayeshgar, S., Hammad, A.: Extending IFC to incorporate information of RFID tags attached to building elements, Advanced Engineering Informatics, 30 (2016) 1, pp. 39-53, https://doi.org/10.1016/j.aei.2015.11.004.

[26] Khan, M.S., Kim, I.S., Seo, J.: A boundary and voxel-based 3D geological data management system leveraging BIM and GIS, International Journal of Applied Earth Observation and Geoinformation, 118 (2023), 103277, https://doi.org/10.1016/j.jag.2023.103277.

[27] Chung, S., Cho, C.S., Song, J., Lee, K., Lee, S., Kwon, S.: Smart Facility Management System Based on Open BIM and Augmented Reality Technology, Applied Sciences, 21 (2021) 11, pp. 1-24, https://doi.org/10.3390/app112110283.

[28] Korkmaz, Ö., Basaraner, M.: Ontology Based Integration of BIM and GIS for the Representation of Architectural, Structural and Functional Elements of Buildings, The International Archives of The Photogrammetry, Remote Sensing and Spatial Information Sciences XLVIII-4/W11, (2024), pp. 49-55, https://doi.org/10.5194/isprs-archives-XLVIII-4-W11-2024-49-2024.

[29] Mignard, C., Nicolle, C.: Merging BIM and GIS using ontologies application to urban facility management in ACTIVe3D, Computers in Industry, 65 (2014) 9, pp.1276-1290, https://doi.org/10.1016/j.compind.2014.07.008.

[30] Mignard, C., Nicolle, C.: SIGA3D: Semantic Combination of IFC and GIS to Support Urban Facilities Management (Chapter), Handbook of Research on E-Business Standards and Protocols, IGI Global, pp. 806-828, 2012, https://doi.org/10.4018/978-1-4666-0146-8.ch037.

[31] Kang, T.W., Hong, C.H.: A study on software architecture for effective BIM/GIS-based facility management data integration, Automation in Construction, 54 (2015) pp. 25-38, https://doi.org/10.1016/j.autcon.2015.03.019.

[32] Cetl, V., Markovinović, D., Šamanović, S., Rezo, M.: Integracija BIM-a i GIS-a, 15. simpozij ovlaštenih inženjera geodezije - Geodezija i vode, Zagreb, pp. 117-124., 2022.

[33] Gao, X., Pishdad-Bozorgi, P.: BIM-enabled facilities operation and maintenance: A review, Advanced Engineering Informatics, 39 (2019), pp. 227-247, https://doi.org/10.1016/j.aei.2019.01.005.

[34] Kameli, M., Hosseinalipour, M., Majrouhi Sardroud, J., Ahmed, S.M., Behruyan, M.: Improving maintenance performance by developing an IFC BIM/RFID-based computer system, Journal of Ambient Intelligence and Humanized Computing, 12 (2021) 6, pp. 3055-3074, https://doi.org/10.1007/s12652-020-02464-3.

[35] Motamedi, A., Saini, R., Hammad, A., Zhu, B.: Role-based access to facilities lifecycle information on RFID tags, Advanced Engineering Informatics, 25 (2011) 3, pp. 559-568, https://doi.org/10.1016/j.aei.2011.03.004.

[36] Motamedi, A., Soltani, M.M., Setayeshgar, S., Hammad, A.: Extending IFC to incorporate information of RFID tags attached to building elements, Advanced Engineering Informatics, 30 (2016) 1, pp. 39-53, https://doi.org/10.1016/j.aei.2015.11.004.

[37] Lin, Y-C., Su, Y-C., Chen, Y-P.: Developing Mobile BIM/2D Barcode-Based Automated Facility Management System, The Scientific World Journal, (2014), pp. 1-16, https://doi.org/10.1155/2014/374735.

[38] Hahn, M., Palmer, R.N., Merrill ,M.S.: Prioritizing Sewer Line Inspection with an Expert System, American Society of Civil Engineers, (2000), pp. 1-9, https://doi.org/10.1061/40430(1999)86.

[39] Hahn, M.A., Palmer, R.N., Merrill, M.S., Lukas, A.B.: Expert System for Prioritizing the Inspection of Sewers: Knowledge Base Formulation and Evaluation, Journal of Water Resources Planning and Management, 128 (2002), pp. 121-129, https://doi.org/10.1061/(ASCE)0733-9496(2002)128:2(121).

[40] Giovanelli, M., Maglionico, M.: Identification of the optimal level of service for sewer networks by means of expert procedure, 11th International Conference on Urban Drainage, Edinburgh, Scotland, UK, 2008.

[41] Ana Jr. E., Bauwens, W.: Sewer Network Asset Management Decision Support Tools: A Review, International Symposium on New Directions in Urban Water Management, Belgium, 2007.

[42] Tagherouit, W. B., Bennis, S., Bengassem, J.: A Fuzzy Expert System for Prioritizing Rehabilitation of Sewer Networks, Computer-Aided Civil and Infrastructure Engineering, 26 (2011), pp. 146-152, https://doi.org/10.1111/j.1467-8667.2010.00673.x.

[43] Al-Zahrani, M.A., Moeid, K.: Locating Optimum Water Quality Monitoring Stations in Water Distribution System, Bridging the Gap, Reston, American Society of Civil Engineers, (2001), pp. 1-9, https://doi.org/10.1061/40569(2001)393.

[44] León, C., Martín, S., Elena, JM., Luque, J.: EXPLORE - Hybrid Expert System for Water Networks Management, Journal of Water Resources Planning and Management, 126 (2000), pp. 65-74. https://doi.org/10.1061/(ASCE)0733-9496(2000)126:2(65).

[45] Moglia, M., Burn, S., Meddings, S.: Decision support system for water pipeline renewal prioritisation, Journal of Information Technology in Construction, 11 (2006), pp. 237-256.

[46] Fares, H., Zayed, T.: Hierarchical Fuzzy Expert System for Risk of Failure of Water Mains. Journal of Pipeline Systems Engineering and Practice, 1 (2010) 1, pp. 53-62, https://doi.org/10.1061/(ASCE)PS.1949-1204.0000037.

[47] Sandeep, K., Rakesh, K.: CLIPS based decision support system for water distribution networks. Drinking Water Engineering and Science, 4 (2011) 1, pp. 37-50, https://doi.org/10.5194/dwes-4-37-2011.

[48] Karasneh, S., Moqbel, S.: Priority-based decision model for rehabilitation of water networks using fahp, Water Conservation & Management, 8 (2024) 1, pp. 37-46.

[49] Petley, D.N., Mantovani, F., Bulmer, M.H., Zannoni, A.: The use of surface monitoring data for the interpretation of landslide movement patterns, Geomorphology, 66 (2006) 1-4 pp. 133-147, https://doi.org/10.1016/j.geomorph.2004.09.011.

[50] Rossi, M., Guzzetti, F., Reichenbach, P., Mondini, A.C., Peruccacci, S.: Optimal landslide susceptibility zonation based on multiple forecasts, Geomorphology, 114 (2010) 3 pp. 129-42, https://doi.org/10.1016/j.geomorph.2009.06.020.

[51] Thiebes, B., Bell, R., Glade, T., Jäger, S., Anderson, M., Holcombe, L.: A WebGIS decision-support system for slope stability based on limit-equilibrium modelling, Engineering Geology, 158 (2013), pp.109-118, https://doi.org/10.1016/j.enggeo.2013.03.004.

[52] Muthu, K., Petrou, M.: Landslide-Hazard Mapping Using an Expert System and a GIS, IEEE Transactions on Geoscience and Remote Sensing, 45 (2007) 2, pp. 522-531, https://doi.org/10.1109/TGRS.2006.885404.

[53] Wan, S., Lei, T-C., Chou T-Y.: A landslide expert system: image classification through integration of data mining approaches for multi-category analysis, International Journal of Geographical Information Science, 26 (2012) 4, pp. 747-770, https://doi.org/10.1080/13658816.2011.613397.

[54] Tsangaratos, P., Loupasakis, C., Nikolakopoulos, K., Angelitsa, V., Ilia, I.: Developing a landslide susceptibility map based on remote sensing, fuzzy logic and expert knowledge of the Island of Lefkada, Greece, Environmental Earth Sciences, 77 (2018) 363, pp. 1-23, https://doi.org/10.1007/s12665-018-7548-6.

[55] Adhikari, I., Baral, A., Zahed, E., Abediniangerabi, B., Shahandashti, M.: Early stage multi-criteria decision support system for recommending slope repair methods, Civil Engineering and Environmental Systems, 38 (2021) 2, pp. 127-144, https://doi.org/10.1080/10286608.2021.1923699.

[56] Albusoda, B.S., Al-Hamdani, D.A., Abbas, M.F.: Dry Density Based on Soil Index Properties by Using Expert System, Key Engineering Materials, 857 (2020), pp. 266-272, https://doi.org/10.4028/www.scientific.net/KEM.857.266.

[57] Mosa, A.M., Taha, M.R., Ismail, A., Rahmat, R.A.O.K.: A diagnostic expert system to overcome construction problems in rigid highway pavement, Journal of Civil Engineering and Management, 19 (2013) 6, pp.846-861, https://doi.org/10.3846/13923730.2013.801905.

[58] Milad, A., Majeed, S.A., Adwan, I., Nasradeen, A.K., Yusoff, N.I.M.: Adaptive neuro fuzzy inference system for predicting flexible pavement distress in tropical regions, Journal of Engineering Science and Technology, 17 (2022) 1, pp. 1-11.

[59] Al-Mansour, A., Lee, K.W.W., Al-Qaili, A.H.: Prediction of Pavement Maintenance Performance Using an Expert System, Applied Sciences, 12 (2022) 10, pp. 1-14, https://doi.org/10.3390/app12104802.

[60] Pereira, H.M., Júnior, J.E.B., Nóbrega, R.A.A.: Geospatial-based decision support system for prioritizing road segments for maintenance and rehabilitation, World Conference on Transport Research Society, 16 (2024), https://doi.org/10.1016/j.cstp.2024.101170.

[61] Jadid, N., Badrah, M.: Decision support system approach for construction materials selection, Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design, pp. 1-7, 2012.

[62] Yang, J., Ogunkah, I.C.B.: A Multi-Criteria Decision Support System for the Selection of Low-Cost Green Building Materials and Components, Journal of Building Construction and Planning Research, 1 (2013) 4, pp. 89-130, https://doi.org/10.4236/jbcpr.2013.14013.

[63] Akadiri, P.O., Olomolaiye, P.O., Chinyio, E.A.: Multi-criteria evaluation model for the selection of sustainable materials for building projects, Automation in Construction, 30 (2013), pp. 113-125, https://doi.org/10.1016/j.autcon.2012.10.004.

[64] Goodarzizad, P., Mohammadi, G.E., Arashpour, M.: Predicting the construction labour productivity using artificial neural network and grasshopper optimisation algorithm, International Journal of Construction Management, 23 (2023), pp. 763-779, https://doi.org/10.1080/15623599.2021.1927363.

[65] Abdolrasol, M.G.M., Hussain, S.M.S., Ustun, T.S., Sarker, M.R., Hannan, M.A., Mohamed, R., et al.: Artificial Neural Networks Based Optimization Techniques: A Review, Electronics (BASEL), 10 (2021) 21, pp. 1-43, https://doi.org/10.3390/electronics10212689.

[66] Zou, J., Han, Y., So, S.S.: Overview of Artificial Neural Networks (Chapter), Artificial Neural Networks: Methods and Protocols, Springer, (2008), pp. 14-22, https://doi.org/10.1007/978-1-60327-101-1_2.

[67] Wilamowski, B.: Neural network architectures and learning algorithms, IEEE Industrial Electronics Magazine, 3 (2009), pp. 56-63, https://doi.org/10.1109/MIE.2009.934790.

[68] Leśniak, A., Juszczyk, M.: Prediction of site overhead costs with the use of artificial neural network based model, Archives of Civil and Mechanical Engineering, 18 (2018) 3, pp. 973-982, https://doi.org/10.1016/j.acme.2018.01.014.

[69] Attalla, M., Hegazy, T.: Predicting Cost Deviation in Reconstruction Projects: Artificial Neural Networks versus Regression, Journal OF Construction Engineering and Management, 129 (2003) 4, pp. 405-411, https://doi.org/10.1061/(ASCE)0733-9364(2003)129:4(405).

[70] ElSawy, I., Razek, M.A.M., Hosny, H.: A Neural Network Model for Construction Projects Site Overhead Cost Estimating in Egypt, International Journal of Computer Science, 8 (2011) 3, pp. 273-283.

[71] Moselhi, O., El-Sawah, H.: Comparative study in the use of neural networks for order of magnitude cost estimating in construction, Journal of Information Technology in Construction, 19 (2014), pp. 462-473.

[72] Yadav, R., Vyas, M., Vyas, V., Agrawal, S.: Development of cost estimating method for bricklayer cost, International Journal of Engineering Research and Technology, (2016), pp. 430-441.

[73] Pessoa, A., Sousa, G., Maués, L., Alvarenga, F., Santos, D.: Cost Forecasting of Public Construction Projects Using Multilayer Perceptron Artificial Neural Networks: A Case Study, Ingeniería e Investigación, 41 (2021) 3, pp. 1-11. https://doi.org/10.15446/ing.investig.v41n3.87737.

[74] Maghrebi, M., Sammut, C., Waller, T.S.: Predicting the Duration of Concrete Operations Via Artificial Neural Network and by Focusing on Supply Chain Parameters, Building Research Journal, 61 (2014), pp. 1-14. https://doi.org/10.2478/brj-2014-0001.

[75] Golizadeh, H., Sadeghifam, A.N., Aadal, H., Majid, M.Z.A.: Automated tool for predicting duration of construction activities in tropical countries, KSCE Journal of Civil Engineering, 20 (2016), pp. 12-22, https://doi.org/10.1007/s12205-015-0263-x.

[76] Aswed, G.K.: Productivity estimating model for bricklayers in construction projects using artificial neural networks, Journal of Engineering Sciences, 9 (2016), pp.183-199.

[77] Al-Zwainy, F.M.S., Rasheed, H.A., Ibraheem, H.F.: Development of the construction productivity estimation model using artificial neural network for finishing works for floors with marble, Journal of Engineering and Applied Sciences, 7 (2012), pp. 714-722.

[78] Cheung, S.O., Wong, P.S.P., Fung, A.S.Y., Coffey, W.V.: Predicting project performance through neural networks, International Journal of Project Management, 24 (2006), pp. 207-215, https://doi.org/10.1016/j.ijproman.2005.08.001.

[79] Alarcón, L.F., Mourgues, C.: Performance Modeling for Contractor Selection, Journal of Management in Engineering, 18 (2002), pp. 52-60, https://doi.org/10.1061/(ASCE)0742-597X(2002)18:2(52).

[80] Zadeh, L.A.: Fuzzy Logic (Chapter), Encyclopedia of Complexity and Systems Science Series, Springer, New York, 2009, https://doi.org/10.1007/978-1-0716-2628-3_234

[81] Hentout, A., Maoudj, A., Aouache, M.: A review of the literature on fuzzy-logic approaches for collision-free path planning of manipulator robots, Artificial Intelligence Review, 56 (2023), pp. 3369-3444, https://doi.org/10.1007/s10462-022-10257-7.

[82] Cho, H.N., Choi, H.H., Kim, Y.B.: A risk assessment methodology for incorporating uncertainties using fuzzy concepts, Reliability Engineering and System Safety, 78 (2002), pp. 173-183, https://doi.org/10.1016/S0951-8320(02)00158-8.

[83] Amiri, M., Ardeshir, A., Zarandi, M.H.F.: Fuzzy probabilistic expert system for occupational hazard assessment in construction, Safety Science, 93 (2017), pp. 16-28, https://doi.org/10.1016/j.ssci.2016.11.008.

[84] Debnath, J., Biswas, A., Sivan, P., Sen, K.N., Sahu, S.: Fuzzy inference model for assessing occupational risks in construction sites, International Journal of Industrial Ergonomics, 55 (2016), pp. 114-128, https://doi.org/10.1016/j.ergon.2016.08.004.

[85] Liu, H.T., Tsai, Y.: A fuzzy risk assessment approach for occupational hazards in the construction industry, Safety Science, 50 (2012), pp. 1067-1078, https://doi.org/10.1016/j.ssci.2011.11.021.

[86] Janackovic, G.Lj., Savic, S.M., Stankovic, M.S.: Selection and ranking of occupational safety indicators based on fuzzy AHP: A case study in road construction companies, The South African Journal of Industrial Engineering, 24 (2013) 3, pp. 1-24, https://doi.org/10.7166/24-3-463.

[87] Seker, S., Zavadskas, E.: Application of Fuzzy DEMATEL Method for Analyzing Occupational Risks on Construction Sites, Sustainability, 9 (2017), pp. 1-19, https://doi.org/10.3390/su9112083.

[88] Oliveros, A.V.O., Fayek, A.R.: Fuzzy Logic Approach for Activity Delay Analysis and Schedule Updating, Journal of Construction Engineering and Management, 131 (2005) pp. 42-51, https://doi.org/10.1061/(ASCE)0733-9364(2005)131:1(42).

[89] Gunduz, M., Nielsen, Y., Ozdemir, M.: Fuzzy Assessment Model to Estimate the Probability of Delay in Turkish Construction Projects, Journal of Management in Engineering, 31 (2015), pp. 1-49, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000261.

[90] Gómez-Cabrera, A., Gutierrez-Bucheli, L., Muñoz, S.: Causes of time and cost overruns in construction projects: a scoping review, International Journal of Construction Management, 24 (2024), pp.1107-1125, https://doi.org/10.1080/15623599.2023.2252288.

[91] Knight, K., Robinson, F.A.: Use of Fuzzy Logic for Predicting Design Cost Overruns on Building Projects, Journal of Construction Engineering and Management, 128 (2002), pp. 503-512, https://doi.org/10.1061/(ASCE)0733-9364(2002)128:6(503).

[92] Gen, M., Lin, L.: Genetic Algorithms and Their Applications (Chapter), Handbook of Engineering Statistics, Springer, London, (2023), pp. 635-674, https://doi.org/10.1007/978-1-4471-7503-2_33.

[93] Katoch, S., Chauhan, S.S., Kumar, V.: A review on genetic algorithm: past, present, and future, Multimedia Tools and Applications, 80 (2021), pp. 8091-8126, https://doi.org/10.1007/s11042-020-10139-6.

[94] Chambers, L.D.: Decoupled Optimization of Power Electronics Circuits Using Genetic Algorithms (Chapter), The Practical Handbook of Genetic Algorithms, Chapman and Hall/CRC, New York, 2000, https://doi.org/10.1201/9781420035568.

[95] Boukhater, C.M., Dakroub, O., Lahoud, F., Awad, M., Artail, H.: An intelligent and fair GA carpooling scheduler as a social solution for greener transportation, 17th IEEE Mediterranean Electrotechnical Conference, (2014), pp. 182-186, https://doi.org/10.1109/MELCON.2014.6820528.

[96] Kumar, V., Pandey, A., Singh, R.: Project success and critical success factors of construction projects: project practitioners' perspectives, Organization, Technology and Management in Construction, an International Journal, 15 (2023), pp. 1-22, https://doi.org/10.2478/otmcj-2023-0001.

[97] Albayrak, G.: Novel Hybrid Method in Time-Cost Trade-Off for Resource-Constrained Construction Projects, Iranian Journal of Science and Technology, Transactions of Civil Engineering, 44 (2020) 2020, pp. 1295-1307, https://doi.org/10.1007/s40996-020-00437-2.

[98] Zhang, Y., Li, X., Teng, Y., Bai, S., Chen, Z.: Two-list genetic algorithm for optimizing work package schemes to minimize project costs, Automation in Construction, 165 (2024), pp. 1-18, https://doi.org/10.1016/j.autcon.2024.105595.

[99] Altanany, M.Y., Badawy, M., Ebrahim, G.A., Ehab, A.: Modeling and optimizing linear projects using LSM and Non-dominated Sorting Genetic Algorithm (NSGA-II), Automation in Construction, 165 (2024), https://doi.org/10.1016/j.autcon.2024.105567.

[100] Tafraout, S., Bourahla, N., Bourahla, Y., Mebarki, A.: Automatic structural design of RC wall-slab buildings using a genetic algorithm with application in BIM environment, Automation in Construction, , 106 (2019), pp. 1-10, http://dx.doi.org/10.1016/j.autcon.2019.102901.

[101] Nili, M.H., Taghaddos, H., Zahraie, B.: Integrating discrete event simulation and genetic algorithm optimization for bridge maintenance planning, Automation in Construction, 122 (2021) 1, pp. 1-20, https://doi.org/10.1016/j.autcon.2020.103513.

[102] Ward, B., Savić, D.A.: A multi-objective optimisation model for sewer rehabilitation considering critical risk of failure, Water Science and Technology, 66 (2012), pp. 2410-2417. https://doi.org/10.2166/wst.2012.393.