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Risk Prediction in Road Infrastructure Projects Considering Project Complexity Coefficients

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ABSTRACT

Risks causing delays in the construction of roads and highways frequently lead to substantial economic and social consequences, with project timelines extending up to three times beyond their initial schedules. These risks not only extend the project timeline but also escalate the overall project execution cost. Despite extensive research on construction-related risks globally, a notable gap remains in studies specifically addressing the risk factors that cause delays in road projects. Analysing completed projects is crucial to derive practical and applicable results, as they offer essential insights into the real-world challenges and risks that may cause timeline extensions and budget escalations. Such an approach ensures that the findings are grounded in actual project outcomes, thereby enhancing their relevance and effectiveness in improving future project planning and risk management. For these reasons, this study aims to analyse 25 project characteristics across 28 completed projects, from which three project complexity coefficients are derived. Additionally, a list of risks is defined based on expert evaluations, and the dominant risks are identified. For each of these dominant risks, a prediction model is constructed using Sugeno fuzzy logic, enabling more accurate and sustainable risk management and mitigation in future projects.

KEYWORDS

risk management; sustainable management; risk prediction; road infrastructure; Sugeno fuzzy logic; project complexity coefficients.

1. INTRODUCTION

Risk is an inherent aspect of large-scale construction projects, encompassing possible challenges in meeting project goals. Risk is highly prevalent in construction projects, necessitating a thorough risk assessment [1]. The continuous rise in both the figure and interconnectedness of the project risks requires a systematic, holistic assessment of risk, leading to structured collective decision processes. According to Samani and Shahbodaghlou [2], multi-valued logic in managing risks produces improved outcomes compared to conventional research methods, as it can effectively delineate the relationships among risks, contributing factors and their consequences [3, 4].

Effective risk management involves understanding the fundamental aspects that contribute to threats to project execution, which are typically consistent across all project types. Commonly, an initial risk assessment phase involves identifying risks. Following identification, a risk analysis is performed to assess the probability of these risks materialising [3, 4]. Risk identification aims to pinpoint latent risks that could influence project objectives positively or negatively.

Vygnanov and Fironov [5] propose a risk management methodology that consists of four key processes: within the planning group, risk identification and assessment are conducted; in the project group, risk mitigation measures are developed; and the management group is responsible for the overall management of risks. Risk represents an uncertain detriment, quantified by its probability of occurrence, that can affect various dimensions of a project, such as cost, schedule or scope. Early identification of risks enables project managers to mitigate potential impacts and aids in the timely delivery of projects. The risk management process includes identifying, analysing and applying strategies to minimise identified risks, which can be effectively achieved through multi-valued reasoning in the management of risks [6–9].

In the context of complex construction projects, a key challenge is how to systematically assess and quantify risks when objective project data are scarce or incomplete. This has led to the frequent application of expert evaluation methods as a reliable tool for supporting risk assessment and decision-making. Recent research also highlights the growing role of artificial intelligence and machine learning techniques, including transformers and tokenisation methods, in improving predictive accuracy in decision-making contexts [10–12]. The expert evaluation method is widely applied in risk assessment and decision-making within infrastructure project management, especially in situations where empirical data are limited. Various studies have combined expert panels, Likert scales and weighted scoring models to assess critical risks and quantify expert opinions, often integrating them into predictive models such as fuzzy inference systems [13–15]. This approach is particularly relevant in complex and variable project environments, where expert judgement helps overcome data limitations. In line with this, the present study incorporates expert input into the calibration of the fuzzy model to ensure that project complexity factors are accurately represented.

In the literature, significant attention is given to the identification and classification of risks [16–18]. Tah and Carr [16] established a risk hierarchy, classifying risks as either external or internal. Chapman [17] identified various risk origins, including the surroundings, industry sector and employers, and identified fifty-eight associated risk factors in construction projects. Lu et al. [18] classified seven categories of risks in construction projects: (1) budget risks, (2) binding and lawful risks, (3) risks associated with subcontractors, (4) labour and protection risks, (5) sociopolitical risks, (6) risks form project designing and (7) unforeseeable event risks.

Table 1 presents a summary of key features and research findings gathered from an extensive analysis of publications, primarily focusing on studies that utilise multi-criteria analysis in risk management and project complexity evaluation. The table highlights significant aspects that informed the methodology of this study, including critical project characteristics, commonly identified risks, and the effectiveness of fuzzy logic in addressing uncertainties within complex construction projects. This structured overview serves as a foundation for understanding the context and relevance of fuzzy approaches in risk prediction, offering a comprehensive reference point for the study's development of predictive models and complexity assessment frameworks.

Table 1 – Summary of key characteristics and research findings from the analysis of publications, with a concentration on multi-criteria studies

Authors	Papers	Year	Approach and methods	Main research findings
Iqbal, Choudhry, Holschemacher, Ali, & Tamošaitienė [19]	Risk Management in Construction Projects	2015	Expert judgement questionnaire	37 most applicable risks were incorporated into the questionnaire. Payment delays received the highest score for the responsibility for delays occurring in construction projects.
Edjossan-Sossou, Galvez, Deck, Al Heib, Verdel, Dupont, Chery, Camargo, Morel [20]	Sustainable Risk Management Strategy Selection Using a Fuzzy Multi-Criteria Decision Approach	2020	Fuzzy multi-criteria decision-making	Risk management strategies are prioritised based on a set of criteria. The results showed that the criteria aggregation approach, the confidence level chosen by the decision-makers, and their attitude affect the ranking.
Antoniou [21]	Delay Risk Assessment Models for Road Projects	2021	Multi-criteria decision-making	The study identified four specific delay factors that predominantly affect Greek road construction projects, for which targeted mitigation strategies were proposed.

Authors	Papers	Year	Approach and methods	Main research findings
Thomas et al. [22]	Modelling and Assessment of Critical Risks in BOT Road Projects	2006	Fuzzy-fault tree analysis	The study presents a risk assessment framework that effectively models and analyses the critical risks associated with Indian BOT road projects, such as traffic revenue risk, land acquisition delays, demand risk and financial closure delays.
Abdolreza Yazdani-Chamzini [23]	Proposing a New Methodology Based on Fuzzy Logic for Tunnelling Risk Assessment	2014	Fuzzy inference system	The use of a fuzzy inference system in assessing risks in tunnel construction has demonstrated considerable potential for precise risk evaluation and prioritisation.
Canesi and Gallo [24]	Risk Assessment in Sustainable Infrastructure Development Projects: A Tool for Mitigating Cost Overruns	2023	Case study	The study successfully developed a risk matrix that predicts a potential cost increase of 7.53% for an infrastructure project, with this estimate deviating by only 1.34% from the actual execution costs, thus effectively mitigating unexpected cost overruns.
Our study	Risk Prediction in Road Infrastructure Projects Considering Project Complexity Coefficients	2025	Fuzzy inference system	This study seeks to analyse 25 project characteristics from 28 completed projects to derive three complexity coefficients, define and identify dominant risks through expert evaluations, and use Sugeno fuzzy logic to construct a prediction model for more accurate risk management and mitigation in future projects.

Based on a review of the literature, it has been observed that existing research lacks a systematic framework for assessing project complexity and predicting dominant civil engineering risks. This research seeks to bridge that discrepancy through the development of a structured approach to evaluating project complexity and identifying key risks. The research analyses a set of critical project characteristics to derive complexity coefficients that represent overall project complexity. Through expert assessments, a comprehensive list of potential risks is established, allowing for the identification of dominant risks that have the most significant impact on project outcomes. To address these risks, the study employs Sugeno fuzzy logic, a powerful method for managing uncertainty and generating precise predictions in complex systems.

This research contributes to the field by offering a novel approach to risk management, combining project complexity assessment with advanced predictive modelling. The results have practical implications for enhancing the reliability and success of construction projects, particularly in managing and mitigating risks that are most likely to affect project outcomes.

2. METHODOLOGY

This study seeks to improve risk management in road and highway construction by evolving the systematic approach for assessing project complexity and forecasting key risks. To achieve this, the research analyses 25 key characteristics from 28 completed projects to derive three complexity coefficients that encapsulate the overall project complexity. Based on expert evaluations, a comprehensive list of potential risks is established, and the dominant risks, which have the most significant impact on project outcomes, are identified.

Risk identification in road construction projects is a crucial component of project management conducted during various phases, most commonly in the early stages of planning and design. In the planning phase, an initial assessment of all potential risks that could impact project success is carried out, including technical, economic, safety and environmental factors. During the design phase, risks are further developed based on specific technical solutions, allowing for a more precise assessment and the development of mitigation strategies. However, the risk identification process is not limited to the initial project stages; it continues throughout the entire project lifecycle, encompassing the construction and operational phases, where new risks may emerge, or existing risks may be redefined depending on changes in circumstances or specific situations on the site.

To address these dominant risks, prediction models are constructed using Sugeno fuzzy logic, a method recognised for its effectiveness in handling uncertainty and providing accurate predictions in complex systems. This research contributes to the field by offering a novel approach to risk management, combining project complexity assessment with advanced predictive modelling. The findings carry practical implications for enhancing the reliability and success of construction projects, especially in the management and mitigation of risks most likely to impact project outcomes.

2.1 TSK system

The Takagi-Sugeno-Kang (TSK) fuzzy inference system (FIS) is a specialised type of fuzzy logic system well-suited for handling complex, non-linear systems; hereafter referred to as the TSK system. This model is particularly valued for its ability to process complex data sets. Unlike traditional logic, which operates on binary values (true or false), fuzzy logic allows for partial membership within sets, providing a way to represent real-world concepts with varying degrees of truth. In a fuzzy logic system, the extent of an element's membership in the group is quantified through the characteristic operation that measures this partial association.

Structure of the TSK system

The TSK system is distinguished by a regulation framework consisting of rules containing an occasion (precursor) and an outcome (successor). Descriptive language parameters are used as the precursor of TSK assertion, whereas the successors are generally expressed as linear functions or fixed values.

The standard TSK principle is formulated as:

If x→A and y→B, then q=f(x, y).

In this context, TSK groups are A and B, and they represent x and y, the input parameters. A sharp function f(x, y) is typically expressed as the linear compound of the TSK groups. The successor may be structured as follows:

$$q = ax + by + c$$

where a, b and c are fixed values.

Conclusion process

The following essential stages were comprised in the TSK system for the conclusion process:

- Linguistic mapping: For each TSK group, precise input values are converted into membership degrees. Each input is allocated a membership degree ranging from 0 to 1, indicating an association level with the relevant TSK group.
- Examination of rules: The precursors of the TSK principles are evaluated to identify the rule strength. The fuzzy intersection operation accomplished this by multiplying the precursor figures.
- Output integration: The output is generated for every rule using the associated successor function, typically a linear function in the TSK system.
- Output defuzzification: The single crisp output is produced by merging the outputs of all rules, which is often done using a weighted arithmetic mean. The weights correspond to the standardised rule strengths.

The final outcome, Q, is calculated by the equation:

$$Q = \frac{\sum(si \times qi)}{\sum si}$$

where:

- si – represents the rule strength of the rule in order of place i-th;
- qi – denotes the outcome from the successor function of the rule in order of place i-th.

This weighted arithmetic mean method guarantees an appropriate reflection of the final outcome that contributes to all engaged rules [25–29].

2.2 Utilised programs and mechanisms

The MATLAB (version 2024) was used in this research to create and implement the TSK logic, taking advantage of its advanced computational capabilities and extensive toolbox for effective data modelling and analysis. Furthermore, SPSS software (version 28.0) [30–32] was utilised for data evaluation, supporting and ensuring the precision and trustworthiness of the study's results.

3. OUTCOME

3.1 Data collection

The study data collection encompasses twenty-eight finished projects that represent significant state roads of the Republic of Serbia associated with the development of the pan-European Road Corridor X. This multimodal transport link runs from Northwest to Southeast Europe. It connects Salzburg (Austria) – Ljubljana (Slovenia) – Zagreb (Croatia) – Beograd (Serbia) – Skopje (North Macedonia) – Thessaloniki (Greece). The main axis is connected to the following cities or areas via four branches:

- Graz (Austria) – Maribor (Slovenia) – Zagreb (Croatia);
- Budapest (Hungary) – Novi Sad (Serbia) – Beograd (Serbia);
- Niš (Serbia) – Sofija (Bulgaria) and further along Corridor IV to Istanbul; and
- Veles (North Macedonia) – Bitola (North Macedonia) – Florina (Greece) and further via Florina – Kozani (via Egnatia) to Igoumenitsa.

The construction of the main axis of Corridor X in the southern part of the Republic of Serbia, covering a total of 74.2 km, was initiated in 2010 and completed in 2024. This segment consists of 10 distinct contracts, each awarded through internationally standardised tendering processes, resulting in 10 individual contracts. Furthermore, two supplementary contracts were implemented to construct auxiliary local roads to accommodate impacted neighbouring populations.

The branch Niš (Serbia) – Sofija (Bulgaria) of Corridor X in the eastern part of the Republic of Serbia, extending over 86 km, was initiated in 2009 and reached completion in 2024. This segment encompassed sixteen distinct contracts executed in alignment with international financial institution standards. The design for these contracts involved building a multi-bridge highway with 7 tunnels. Conditions of Contracts were formalised under the so-called Pink FIDIC, which represents Red FIDIC Harmonised by the Banks. Procurement processes complied with the frameworks established by the multilateral bank rules and guidelines for procurement in force during the period of the financial agreement.

Project characteristics

During the evaluation, a rigorous investigation of specific determinants that critically affect the implementation and outcome of the project is paramount. The framework of twenty-five characteristics of the project is established to enhance the predictive accuracy regarding the probability of particular risk occurrence.

This framework emerged from an extensive literature review complemented by a dedicated two-day expert interview session on risk management. The session engaged 14 engineers and specialists with substantial expertise in road infrastructure projects, both within Serbia and internationally. To ensure a comprehensive risk assessment, the study incorporated a diverse panel of experts from multiple disciplines relevant to infrastructure projects. The expert team included not only technical specialists but also project managers, as well as hydrotechnical engineers, structural engineers, linear infrastructure engineers, electrical engineers, urban planners, geotechnical engineers, environmental engineers, social experts and procurement specialists. Many of these experts held pivotal roles in the analysed projects, acting as the Employer's Representatives, Engineer and Implementation Consultant. Diversity among experts allowed the research to encompass a broad range of perspectives, addressing technical, environmental, social and procedural aspects of risk. The inclusion of project management expertise further enriched the evaluation, enabling a nuanced assessment of risks that extends beyond a purely technical focus and provides a well-rounded understanding of the challenges affecting project outcomes.

The characteristics delineated in this framework furnish a comprehensive perspective on the essential elements required for effective project evaluation and risk management. For the 28 completed projects under analysis, these identified project characteristics are systematically summarised in *Table 2*.

Table 2 – Summary of project characteristics and detailed descriptions (Source: [33]*)*

Characteristic	Description
Accepted contract amount [€]	Denotes the contractually accepted sum outlined in the Letter of Acceptance for the execution and completion of the Works, including the remediation of any identified defects. Quantifications are provided in euros.
Time for completion [days]	Indicates the allocated timeframe for the completion of the Works, measured from the Commencement Date. Values are expressed in days.
Landslides along the route [1, 2, 3 or 4]	Classification based on geological survey findings: 1 – absence of landslides, 2 – sporadic occurrence of landslides, 3 – moderate frequency of landslides, 4 – high frequency of landslides.
Archaeological sites along the route [1, 2, 3 or 4]	Classification based on the presence of cultural assets: 1 – no recorded assets, 2 – assets in proximity, 3 – preliminary investigation required, 4 – archaeological excavation necessary.
Population density in the future route zone [n/km²]	Defined as the population density, calculated by dividing the number of inhabitants divided by the area of the zone of influence (a 5 km radius around the section).
Difference between the highest and lowest points on the route [m]	Represents the elevation range between the highest and lowest points within the terrain, serving as an indicator of topographic complexity. Classified terrain types are as follows: plain (≤ 50 m), hilly (50 – 150 m) and mountainous (≥ 150 m).
Section length [km]	Denotes the total length of the horizontal alignment as specified in the road layout plan.
Per cent of length of embankments on route [%]	Represents the ratio of the cumulative embankment length to the overall section length, expressed as a percentage.
Per cent of length of bridges on route [%]	Indicates the proportion of the total bridge length relative to the section length, expressed as a percentage.
Per cent of length of cuts on route [%]	Represents the proportion of the total length of cuts relative to the section length, expressed as a percentage.
Per cent of length of tunnels on route [%]	Denotes the ratio of the total tunnel length to the section length, expressed as a percentage.
Maximum height of cuts [m]	Represents the maximum distance between the natural terrain and the vertical alignment of the road, serving as an indicator of the need for cuts versus tunnels.
Maximum height of embankments [m]	The highest distance between the road alignment and the ground elevation, indicating the need for embankments versus bridges.
Predominant material category along the route [A-1 to A-7]	Soil and soil-aggregate mixtures are classified according to the AASHTO (American Association of State Highway and Transportation Officials) Soil Classification System, which organises soil types based on their suitability for roadway and construction applications.
Number of collisions (box culvert, overpass, watercourse, utilities) [n]	Number of collisions with local infrastructure, watercourses and utilities as identified in the layout plan.
Type of foundation [shallow or deep]	Classification of foundation type based on soil resistance: shallow (e.g. strip foundations) or deep (e.g. pile foundations).
Whose contractual obligation is to prepare the Project for Execution [Employer or Contractor]	Indicates whether the Employer or Contractor is responsible for providing the Project for Execution.
Level of land expropriation completion at the time of tender announcement [%]	Represents the percentage of land expropriation parcels completed relative to the total parcels requiring expropriation.
Is the designer a state-owned company [yes or no]	Denotes whether the designer is a state-owned company, a factor that may influence the quality of project documentation and levels of accountability.
Number of amendments and clarifications to tender documents [n]	Represents the number of amendments and additions made to the tender documents, which can affect the overall duration of the tendering process.
Number of submitted bids [n]	Indicates the level of interest from bidders and may affect the review time and likelihood of appeals.

Characteristic	Description
Is the price adjustment for changes in cost contracted [yes or no]	Specifies whether the contract incorporates a Price Adjustment for Changes in Cost clause, influencing adjustments in response to cost fluctuations.
Per cent of contractual advance payment [%]	Denotes the percentage of the advance payment relative to the Accepted Contract Amount, impacting the Contractor's cash flow.
Whose contractual obligation is to provide borrow pits for material [Employer or Contractor]	Indicates whether the Employer or Contractor is responsible for providing borrow pits for material, affecting risk allocation.
Whose contractual obligation is to provide a material disposal area [Employer or Contractor]	Indicates whether the Employer or Contractor is responsible for providing the material disposal area, affecting risk allocation.

Formation of project complexity coefficients

The formation of the complexity coefficient in the context of road construction involves the quantitative assessment and aggregation of specific road characteristics to provide insight into the project's complexity. Experts thoroughly examined and unanimously defined the project complexity coefficients. Through detailed analysis and collaboration, they identified and agreed upon the specific characteristics that make up each coefficient, ensuring that these measures accurately reflect the various challenges associated with the project. Their consensus underscores the reliability and validity of these coefficients in assessing project complexity. The three key complexity coefficients are the environment coefficient, the contractual coefficient and the design coefficient. Each of these is defined by a set of characteristics that are analysed in detail.

The environment coefficient comprises the following characteristics: frequency of landslides along the proposed route, presence of archaeological sites, population density within the projected route zone, vertical elevation range from the maximum to the minimum elevation coordinates, primary soil type throughout the alignment, and the amount of structural intersections (e.g. box culvert, overpasses, watercourses and utility crossings).

The contractual coefficient incorporates attributes related to contractual conditions, including: accepted contract amount, allocated project duration, the responsible entity for the preparation of the design for execution, degree of land acquisition finalisation during tender release, modifications and clarifications amount in tender documentation, total bids submitted, the presence of price adjustment clauses for cost fluctuations, advance payment percentage, accountability for sourcing borrow pits, and responsibility for the provision of material disposal areas.

The design coefficient encompasses key design-related metrics: section length, proportion of embankment length, bridge length, cut length and tunnel length relative to the total route length, maximum cut and embankment heights, foundation type, and whether the designer company is government-owned.

Determining the impact of project characteristics on project execution

For the purpose of parameter evaluation, an initial interview and panel discussion were conducted, during which experts defined a list of parameters. Subsequently, they carried out an evaluation of each project parameter. The evaluation was performed using a Likert scale (ranging from 1 to 7), where the ratings reflected the degree of impact of each parameter on the extension of time (EoT) and the increase in contract price (ICP). A rating of 1 indicated a minimal influence of the project parameter on time extensions and cost increases, whereas a rating of 7 signified the maximum impact, i.e. the most significant potential effect. Experts assessed each project parameter based on their qualitative understanding of its effect on EoT and ICP, with the option to assign the same rating to different parameters if they deemed them to have an equivalent impact. This flexibility enhances the evaluation process, allowing experts to rank project characteristics without compromising the accuracy of their assessments.

The experts' assessment ($\bar{U}_p^{EoT}$) of the specific impact of each parameter on EoT represents the arithmetic mean of all ratings:

$$\bar{U}_p^{EoT} = \frac{\sum_1^{14} U_p^{EoT}}{14}$$

where p is the parameter index.

In the same manner, the final expert assessment ($\bar{U}_p^{ICP}$) for the specific impact of each parameter on ICP was determined.

Based on the obtained mean values, the final rating for each individual parameter (Ep) can be calculated using the following formula:

$$E_p = \omega_1 \times \bar{U}_p^{EoT} + \omega_2 \times \bar{U}_p^{ICP}$$

where:

— ω_1 and ω_2 – weighting coefficients (weights) that reflect the relative importance of each parameter.

In the given example, both factors have equal importance, hence: $\omega_1 = \omega_2 = 1$. The outcomes are presented in *Table 3*.

Table 3 – Impact rating values of the project characteristics on project performance

Group	Project characteristics	Score Ep
Environment	Number of collisions (box culvert, overpass, watercourse, utilities)	10.86
	Landslides along the route	5.06
	Population density in the future route zone	4.31
	The difference between the highest and lowest points on the route	10.88
	Predominant material category along the route	4.05
	Archaeological sites along the route	4.23
Contractual	Accepted contract amount	11.49
	Is the price adjustment for changes in cost contracted	3.77
	Number of submitted bids	3.46
	Time for completion	11.38
	Whose contractual obligation is to prepare the project for execution	3.88
	Number of amendments and clarifications to tender documents	3.57
	Per cent of contractual advance payment	3.60
	Whose contractual obligation is to provide borrow pits for material	3.01
	Whose contractual obligation is to provide a material disposal area	3.54
	Level of land expropriation completion at the time of tender announcement	3.79
Design	Per cent of the length of the tunnels on the route	4.03
	Maximum height of cuts	11.37
	Section length	10.63
	Per cent of the length of cuts on the route	11.04
	Maximum height of embankments	10.92
	Type of foundation	3.89
	Per cent of the length of embankments on the route	10.55
	Per cent of the length of bridges on the route	10.40
	Is the designer a state-owned company	3.74

The basis of this table is sourced from: [33]

Following the analysis and compilation of results, experts reached a consensus that the assigned ratings accurately and reliably reflect the relative influence of project characteristics on both criteria. This consensus confirms the reliability and validity of the methodological approach. Additionally, this approach facilitates straightforward ranking and interpretation of results through mathematical and statistical analysis.

Determination of project complexity coefficients

Before calculating the coefficient of project complexity, it is necessary to normalise the values of the project characteristics Pj. Pj represents the normalised value of the j-th project characteristic. In project management, normalisation is used to bring different characteristics, which may have varying units and scales, onto a common level, enabling comparison and analysis. The normalised value Pj is calculated using min-max normalisation, which transforms the values to fall within the range of 0 to 1. This process is carried out as follows:

$$P_j = \frac{Pi - Pmin}{\text{Pmax} - Pmin}$$

where:
- P_j – normalised characteristics of the j-th contract value;
- P_i – initial (or raw) characteristics of the j-th contract value;
- P_{min} – minimum value of that characteristic among all the projects under consideration;
- P_{max} – maximum value of that characteristic among all the projects under consideration.

All project characteristics are assigned numerical values in a manner that ensures a direct correlation between characteristics rating and project complexity coefficient, such that a higher characteristics rating corresponds to a greater project complexity coefficient. Let K_1, K_2 and K_3 be the three project complexity coefficients. Each complexity coefficient Ki can be calculated based on n project characteristics as follows:

$$K_i = \sum_{j=1}^{n} (\text{Pj} \times \text{Ep})$$

where:
- K_i – project complexity coefficient (for i=1,2,3);
- P_j – normalised characteristic of the j-th contract value;
- E_p – evaluation of the contract characteristic in order of place j-th;
- n – total number of project characteristics.

The three project complexity coefficients are: environment coefficient, contractual coefficient and design coefficient. Project complexity coefficients are organised hierarchically, ranging from the least to the most significant, with the initial coefficient having the lowest average value and the final coefficient exhibiting the highest average value. The resulting values are influenced by the project characteristics that comprise each of these three coefficients, the expert assessment of the significance of each project characteristic (*Table 3*), and the number of project characteristics that contribute to the overall project complexity coefficient. This structured approach ensures that the most critical aspects of project complexity are accurately weighted and considered in the analysis. The coefficient of project complexity for realised projects is shown in *Table 4*.

Table 4 – Coefficients of project complexity for realised projects

Project	Environment coefficient	Contractual coefficient	Design coefficient
1	9.8282	19.0560	38.2486
2	10.3472	19.4571	32.7270
3	3.8140	18.6284	25.3071
4	7.5417	19.9699	25.7173
5	13.4643	22.0857	39.3992
6	9.6375	20.4126	43.8757
7	4.3130	18.5824	22.4006
8	5.0405	17.8525	24.5930
9	5.5642	17.5643	37.6964

Project	Environment coefficient	Contractual coefficient	Design coefficient
10	5.0042	16.9464	35.1025
11	1.7089	11.6488	27.4665
12	7.5219	10.1725	20.3659
13	10.2059	19.8770	41.2720
14	15.6353	19.1536	45.7632
15	7.0392	9.3075	25.7500
16	3.6461	17.4882	25.0633
17	8.9107	19.0148	34.9094
18	7.5243	21.4177	45.2424
19	13.7522	23.3569	52.4325
20	15.1667	10.8083	58.6951
21	4.0515	17.4359	15.8753
22	4.1444	18.3224	36.9475
23	6.2233	13.3695	39.7772
24	9.9153	18.4015	36.7102
25	11.6832	19.2720	18.4551
26	9.8435	10.8548	46.1938
27	9.8435	9.9405	46.1938
28	6.1359	19.9621	25.6578

The results presented in *Table 4* illustrate the variation in project complexity coefficients across the analysed projects. In general, higher values of the design coefficient, for example, values above 35, indicate a project characterised by significant technical challenges, such as complex design requirements, the use of advanced technologies or demanding construction conditions. Conversely, lower values, for example, below 25, suggest technically less complex projects. Similarly, higher values of the contractual coefficient point to projects with more complex contractual frameworks, potentially involving numerous stakeholders, intricate contractual terms or complex risk-sharing mechanisms. The environment coefficient reflects environmental-sensitivity and regulatory constraints, where higher values denote projects located in environmentally demanding areas or those subject to stricter environmental regulations. Overall, projects with high coefficients in all three categories are generally considered complex and may require more intensive management and risk mitigation strategies. These coefficients provide valuable insight for project managers, allowing them to assess the complexity level at an early stage and plan accordingly.

Selection of the most significant risks

This study's primary objective is forecasting the most significant risks influencing contract implementation, which is achieved by utilising a project complexity coefficient. *Table 5* illustrates the percentage of each key risk occurrence across completed projects. Through an extensive analysis of publications, expert evaluations and risk frequency examination in previously executed projects, five predominant risks were selected for detailed examination.

Table 5 – Percentage of occurrence of selected dominant risks in completed projects

Project	**Risk 1.1. Non-compliance of the project with environmental conditions due to inappropriate design bases.**	**Risk 1.11. Inapplicable project documentation for high cuts, including tunnel portals.**	**Risk 1.9. Unresolved collisions with existing infrastructure facilities (underground installations, pipelines, local roads, railways, etc.).**	**Risk 1.5. Delays in the production or changes in project documentation during execution.**	**Risk 1.4. Non-compliance in parts of the project documentation.**
1	7.53	23.01	17.57	3.77	7.95
2	15.63	14.06	11.98	2.60	13.02
3	21.79	21.79	0	0	0
4	21.05	6.32	5.26	5.26	8.42
5	11.86	35.57	6.19	4.12	0
6	11.38	0.60	10.78	7.78	10.78
7	6.67	7.41	19.26	5.19	4.44
8	14.06	7.03	18.75	2.34	7.03
9	17.09	0	2.56	13.68	17.09
10	9.24	0	20.17	0	5.88
11	13.79	0	24.14	6.90	3.45
12	0	0	0	0	7.69
13	18.54	25.28	9.55	7.30	1.69
14	7.84	32.68	9.80	3.92	0.65
15	0	0	0	87.50	0
16	10.59	5.88	0	10.59	5.88
17	4.00	10.67	14.67	9.33	13.33
18	10	5.88	9.41	3.53	14.12
19	3.90	3.90	25.97	3.90	11.69
20	25.87	8.39	3.50	3.50	4.90
21	14.29	14.29	17.86	0	0
22	16.00	0	12.00	20	4.00
23	6.82	0	18.18	2.27	10.23
24	0	8.00	40	0	0
25	0	0	12.50	0	0
26	37.50	0	25.00	0	12.50
27	8.33	5.95	5.95	1.19	9.52
28	3.80	3.80	2.53	6.33	7.59

The results presented in *Table 5* highlight the frequency of occurrence of the five selected dominant risks across 28 completed projects. The analysis reveals that "Risk 1.11. Inapplicable project documentation for high cuts, including tunnel portals" and "Risk 1.1. Non-compliance of the project with environmental conditions due to inappropriate design bases" show particularly high occurrence rates in several projects, indicating that deficiencies in project documentation and environmental considerations are common challenges in infrastructure projects. Additionally, "Risk 1.9. Unresolved collisions with existing infrastructure facilities" also demonstrates a notable frequency, confirming its relevance as a critical factor that can disrupt project execution. The variation in percentages across projects suggests that while certain risks are systemic, others are more context-dependent, influenced by project-specific conditions. This ranking helps identify which risks require the most attention in future projects.

3.2 Predictive analysis of risk in Serbian road infrastructure projects: Case study analysis

The suggested approach was implemented to predict risks and estimate potential increases in accepted contract amount and extensions of time for completion in the construction of roads and highways [34, 35]. The TSK system was chosen because of its computational efficiency and precision in constructing models that are precise, using outcome representations that are linear and multivariable. This case study specifically targets the construction of roads and highways in Serbia, where data for system training and testing the system were sourced from 28 projects across the country. Data from 25 of these projects were utilised for fuzzy inference system (FIS) development and training. For validation, the data from three additional projects were used. The developed fuzzy inference system comprises 3 input variables and 7 output variables (as illustrated in *Figure 1*).

The inputs of the developed TSK fuzzy inference system, as previously defined, are three project complexity coefficients (the environment parameters coefficient, the contractual parameters coefficient and the design parameters coefficient). These coefficients represent aggregated indicators that describe the complexity level of a project in terms of environmental, contractual and technical factors.

The outputs of the TSK fuzzy inference system, as shown in *Figure 1*, consist of two project-level indicators and five critical risk factors. The project-level indicators are extension of time (EoT) and increase in accepted contract price (ICP), which represent two major consequences of risk occurrence in road infrastructure projects. In addition, the system outputs include five selected dominant risks, identified through expert assessment and frequency analysis based on data from 28 completed infrastructure projects:

— Risk 1.1. Non-compliance of the project with environmental conditions due to inappropriate design bases,
— Risk 1.11. Inapplicable project documentation for high cuts, including tunnel portals,
— Risk 1.9. Unresolved collisions with existing infrastructure facilities (underground installations, pipelines, local roads, railways, etc.),
— Risk 1.5. Delays in the creation or changes in project documentation during execution and
— Risk 1.4. Non-compliance in parts of the project documentation.

The selected risks were chosen based on their high frequency and significant impact on project performance, particularly regarding time delays and cost overruns (EoT and ICP), as evidenced in the analysed data and expert opinions.

For generating a fuzzy inference system (FIS) based on a dataset using subtractive clustering in MATLAB, the “genfis2” function was used. This approach enables the automatic determination of rules and membership functions based on the input data. Subtractive clustering analyses the data and identifies cluster centres. Each cluster is then used to create fuzzy rules. Gaussian membership functions were selected to represent the input variables, while linear functions were applied to model the seven output variables. The use of Gaussian functions enables smooth and continuous transitions between fuzzy sets, which is essential for capturing the inherent uncertainty of complex projects. Compared to alternative membership functions, such as triangular or trapezoidal, Gaussian functions demonstrate greater robustness to noise in input data, resulting in enhanced model stability under real-world conditions. Moreover, their differentiability across the entire domain supports more efficient optimisation and fine-tuning of fuzzy logic systems. On the output side, linear functions were chosen due to their computational efficiency, offering faster processing than more complex nonlinear alternatives. In the context of a Sugeno-type fuzzy inference system, linear output functions streamline the defuzzification process, ensuring that risk probabilities are derived quickly and effectively [13].

The “genfis2” function is particularly useful for quickly generating an FIS from data without the need for manual adjustment of rules and membership functions. However, it requires careful tuning of the clustering radius, i.e. the cluster density parameter, to achieve optimal model accuracy. This parameter determines the cluster size when applying the subtractive clustering algorithm. A larger radius value results in fewer but larger clusters, whereas a smaller radius value leads to a greater number of smaller clusters and, consequently, a larger number of fuzzy rules. Normal distribution membership functions were utilised for input parameters, allowing effective simulation of the data entries. Outputs were represented by linear functions, enabling an accurate, robust simulation of results. The principles were designed as “IF-THEN” propositions with mathematical expressions, ensuring a balance between flexibility and accuracy in the modelling process.

The data utilised for generating or training the fuzzy inference system were structured in a database, with the first three columns (A, B and C) containing input variable data and the subsequent seven rows (D to J) containing output variable data. Based on the data, 25 fuzzy rules were generated. The system can be enhanced by expanding the training database with additional data, as this will provide a broader variable span through TSK principles.

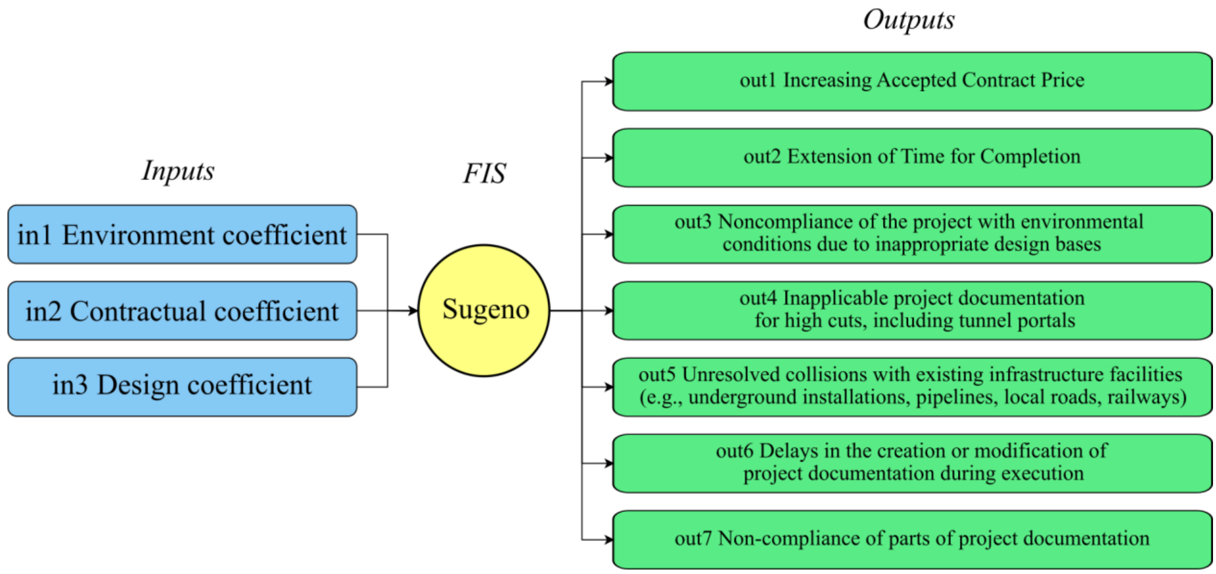

Figure 1 – Structure of the TSK system

The assessment of the generated FIS was conducted using data from actual projects in Serbia. *Table 6* provides the output data obtained from the FIS alongside the corresponding data from the real-world system, specifically from these three projects.

Table 6 – The evaluation results

Outputs	From a real project			From FIS			Deviation [%]			Average deviation [%]
	Project 1	*Project 2*	*Project 3*	*Project 1*	*Project 2*	*Project 3*	*Project 1*	*Project 2*	*Project 3*	
Output 1 (ICP)	105.074	146.613	116.974	99.090	143.143	123.034	5.695	2.366	5.180	4.414
Output 2 (EoT)	71.644	205.342	59.667	65.247	198.223	58.482	8.927	3.467	1.985	4.793
Output 3 (1.1.)	14.063	3.896	8.333	17.342	3.256	8.234	23.321	16.437	1.195	13.651
Output 4 (1.11.)	7.031	3.896	5.952	7.501	2.9896	5.405	6.681	23.287	9.203	13.057
Output 5 (1.9.)	18.750	25.974	5.952	17.163	25.606	5.592	8.464	1.418	6.060	5.314
Output 6 (1.5.)	2.344	3.896	1.190	1.594	3.345	1.112	31.966	14.147	6.630	17.581
Output 7 (1.4.)	7.031	11.688	9.524	7.852	9.852	8.9832	11.685	15.707	5.677	11.023

Table 6 presents a comparison between the actual values obtained from three completed projects and the outputs generated by the FIS model. The "Deviation [%]" columns indicate the percentage difference between the real project data and the FIS predictions for each output, while the "Average deviation [%]" column provides the mean deviation across all three projects for each output variable. Based on engineering judgement and relevant literature, deviations below 10% are generally considered acceptable for early-stage project planning, as they provide a sufficiently reliable basis for risk-informed decision-making [13, 36, 37]. In this analysis, most outputs fall within or close to this acceptable range, with the exception of Output 6 (1.5.), which shows a higher deviation (average of 17.58%). This deviation is interpreted as potentially problematic and signals the need for model refinement, particularly through additional training and adjustment of membership functions. On the other hand, the lowest deviations are observed for the ICP and EoT outputs (Output 1 and Output 2), indicating a higher reliability of the model in predicting these key project indicators. Based on the obtained results, it can be concluded that the developed TSK system exhibits an average deviation of 9.98% in prediction for the selected test projects, which is reasonable given the complexity of the task. From a practical perspective, this level of accuracy is considered satisfactory in the initial phase of project planning [38].

The most significant deviation was noted in the predictions for out6, while it is the smallest for out1. To enhance prediction accuracy, additional training of the FIS, coupled with precise adjustments to the membership functions of input variables and refinement of inference rules, is required.

Application of the TSK model for risk group ranking

The results obtained through the developed TSK fuzzy model methodology can also be effectively used for risk ranking. In road infrastructure projects, risk ranking is of crucial importance as it enables the definition of priorities for undertaking appropriate preventive measures. By applying the TSK model and analysing the obtained coefficients, it is possible to create a ranking list of risk groups. In this way, a customised ranking can be generated for each project, where the model allows, for example, the determination of the relative importance and priority of action for each of the five defined risk groups, contributing to more efficient risk management and cost optimisation.

To facilitate a comparative analysis of the model outputs, three infrastructure projects were selected, each characterised by notable differences in input parameters, specifically the complexity coefficients. The selected projects exhibit varying values of the environmental parameters coefficient, contractual parameters coefficient and technical parameters coefficient, with the aim of testing the model's capability to consistently predict the impact of risks on the ICP and to rank them under diverse conditions. Furthermore, one of the analysed projects includes an outlier in the dataset, allowing for the evaluation of the model's robustness and its capacity to manage extreme values. Following the conducted analyses, the results for the top ten key risks were obtained for each project. The risks are ranked in descending order from those with the greatest impact on the ICP to those with the least influence:

Table 7 – Ranking of the top ten risks according to their influence on ICP

Project 1			***Project 2***			***Project 3***		
Environment coefficient	*Contractual coefficient*	*Design coefficient*	*Environment coefficient*	*Contractual coefficient*	*Design coefficient*	*Environment coefficient*	*Contractual coefficient*	*Design coefficient*
5.0405	17.8525	24.593	13.7522	23.3569	52.4325	3.6461	17.4882	25.0633
1.11. Inapplicable project documentation for high cuts, including tunnel portals. 1.1. Non-compliance of the project with environmental conditions due to inappropriate design bases. 1.5. Delays in the production or changes in project documentation during execution. 2.7. Exchange rate instability and resource price spikes. 1.9. Unresolved collisions with existing infrastructure facilities (underground installations, pipelines, local roads, railways, etc.). 1.6. Incorrect Bill of Quantities of works. 1.7. Insufficiently examined and imprecisely determined locations, as well as available quantities of materials in borrow pits. 3.5. Equipment failures and obsolete machinery. 7.3. Unsolved Claims, Variations and VEPs. 1.10. Inadequate design of riverbeds and stormwater treatment.			1.11. Inapplicable project documentation for high cuts, including tunnel portals. 1.6. Incorrect Bill of Quantities of works. 1.1. Non-compliance of the project with environmental conditions due to inappropriate design bases. 2.7. Exchange rate instability and resource price spikes. 1.5. Delays in the production or changes in project documentation during execution. 3.5. Equipment failures and obsolete machinery. 7.3. Unsolved Claims, Variations and VEPs. 1.10. Inadequate design of riverbeds and stormwater treatment. 7.4. High complexity of the project (scope of works, topography, access restrictions, new technologies, etc.). 1.9. Unresolved collisions with existing infrastructure facilities (underground installations, pipelines, local roads, railways, etc.).			1.11. Inapplicable project documentation for high cuts, including tunnel portals. 1.6. Incorrect Bill of Quantities of works. 2.7. Exchange rate instability and resource price spikes. 1.1. Non-compliance of the project with environmental conditions due to inappropriate design bases. 1.5. Delays in the production or changes in project documentation during execution. 4.6. Delay in handing over (parts of) the construction site to the contractor. 1.7. Insufficiently examined and imprecisely determined locations, as well as available quantities of materials in borrow pits. 1.10. Inadequate design of riverbeds and stormwater treatment. 7.3. Unsolved Claims, Variations and VEPs. 1.8. Failure to provide adequate locations for deposit areas for excavated materials.		

The results in *Table 7* clearly illustrate the model's capacity to effectively rank key risks according to their impact on ICP across different project scenarios. In all three projects, the TSK model consistently identifies "Inapplicable project documentation for high cuts, including tunnel portals" and "Incorrect Bill of Quantities of works" as top-ranked risks, confirming their dominant influence regardless of project-specific parameters. The ranking further shows that certain risks, such as "Exchange rate instability and resource price spikes" and "Unsolved Claims, Variations and VEPs", maintain high positions across multiple projects, emphasising their broad relevance. However, the appearance of risks unique to individual projects, such as "Delay in handing over (parts of) the construction site to the contractor" in Project 3, indicates the model's sensitivity to varying project contexts. The established ranking allows for the clear prioritisation of risks, ensuring that risks with the greatest potential to affect the ICP are systematically identified. This provides decision-makers with a structured basis for targeted risk management actions.

4. CONCLUSIONS

This study has successfully developed a systematic approach to risk prediction in road infrastructure projects by analysing 25 project characteristics across 28 completed projects. From this analysis, three project complexity coefficients were derived, providing a comprehensive measure of project complexity. A list of potential risks was defined based on expert evaluations, and the dominant risks with the most significant impact on project outcomes were identified.

Using Sugeno fuzzy logic, prediction models were constructed for each of the dominant risks, leading to the successful prediction of the five most common risks encountered in infrastructure projects. These models demonstrate the effectiveness of Sugeno fuzzy logic in handling complex, non-linear data and provide valuable insights for more accurate risk management and mitigation in future projects. This approach establishes a robust framework for improving the reliability and success of road infrastructure projects through proactive mitigation of potential risks.

Additionally, the model was extended to include a ranking of risk groups based on their influence on project outcomes, particularly on ICP. The results highlighted that risks related to project documentation deficiencies and unresolved collisions with existing infrastructure were consistently ranked highest, confirming their systemic nature. This ranking provides project managers with a clear prioritisation of risks, helping to focus preventive measures on the most critical threats to project success.

These study findings bear essential practical implications for the effective management of road infrastructure projects. By utilising the developed prediction models based on Sugeno fuzzy logic, project managers and engineers can anticipate and mitigate the most common risks before they impact the project's progress. The derived project complexity coefficients enable better resource allocation, scheduling and contingency planning, ultimately leading to more efficient project execution and reduced likelihood of costly delays or failures. The evaluation of model performance showed that an average deviation of approximately 10% between the model outputs and real project data is acceptable for project assessment at early planning stages, while deviations exceeding 15% are considered problematic and require model refinement. This proactive approach to risk management enhances the overall reliability and success of infrastructure projects.

While the use of expert evaluation in this study has provided valuable insights for assessing the impact of project characteristics on key project indicators (EoT and ICP), certain limitations should be acknowledged. The results depend on the subjective judgement of a selected panel of experts, which, despite their experience and qualifications, may introduce biases or variability in the assessment process. Moreover, the applied variant, based on a single-round scoring using a Likert scale, may limit the depth of consensus that could be achieved through iterative methods, such as the Delphi technique. Therefore, although the outcomes are robust for early-stage project assessments, caution is recommended when generalising the findings to projects outside the analysed context or when applying the results without further expert consultation.

Future research could expand on this study by incorporating a larger and more diverse dataset, including projects from various regions and environments, to enhance the generalisability of the findings [39–44]. Furthermore, incorporating more sophisticated machine learning methods in conjunction with Sugeno fuzzy logic has the potential to enhance the precision of risk prediction models. Research could also explore the dynamic nature of risks over the project lifecycle, developing models that can adapt to changes in project conditions. Additionally, future research should aim to include a broader range of expert disciplines, such as finance specialists, to explore potential differences in risk assessment across various fields and to yield insights evaluated from multiple perspectives. It would also be beneficial for future studies to consider preventive measures from the perspective of contractors, ensuring a more comprehensive approach to risk mitigation.

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