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Forecasting project success in the construction industry using adaptive neuro-fuzzy inference system

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ABSTRACT

Project managers often find it a challenge to successfully manage construction projects. As a result, understanding, evaluating, and achieving project success are critical for sponsors to control projects. In practice, determining key success factors and criteria to assess the performance of construction projects and forecast the success of new projects is difficult. To address these concerns, our objective is to go beyond the efficiency-oriented project success criteria by considering both efficiency- and effectiveness-oriented measures to evaluate project success. This paper contributes to existing knowledge by identifying a holistic and multidimensional set of project success factors and criteria using a two-round Delphi technique. We developed a decision support system using the Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast the success of mid- and large-sized construction projects. We gathered data from 142 project managers in Australia and New Zealand to implement the developed ANFIS. We then validated the constructed ANFIS using the K-fold cross-validation procedure and a real case study of a large construction project in Western Australia. The forecasting accuracy measures R^2=0.97461, MAPE = 2.57912%, MAE = 1.88425, RMSE = 2.3610, RRMSE = 0.03149, and PI = 0.01589 suggest that the developed ANFIS is a very good predictor of project success.

KEYWORDS

Success factors; success criteria; construction industry; medium and large projects; forecasting; aNFIS; Delphi technique

Introduction

Project success is the highly desired outcome for any project. It is often complicated to define the outcomes of successful projects and how to accomplish them (Ahmad et al. 2022). This is partially due to different stakeholders interpreting project success differently because their requirements and expectations differ (Bond-Barnard et al. 2018). Large-scale construction projects are complex and expensive and may cost billions of dollars (Wang et al. 2023). Considering the direct impact of the construction industry on the quality of life and development of nations, project success in this industry has significant financial implications for economies worldwide including Australia and New Zealand (Lin et al. 2023; Zaman et al. 2023). For example, this industry in Australia generated over AU $367.2 billion in revenue in 2022 which contributes around 9% to Australia's gross domestic product (GDP). It is expected that this industry will grow at a rate of 2.4% per annum from 2019 to 2024. The construction industry employed 1,185,100 people in 2022, and the anticipated level of employment in this industry is 1,263,900 people in 2025 (Australian Industry and Skills Committee 2022a). When the size of a project becomes larger, inevitably, more and more stakeholders are involved, and multidisciplinary collaboration is required (Ribeiro et al. 2013). Poor and ineffective stakeholder management can cause several problems, e.g. unclear scope definition, and inappropriate resource allocation, which might lead to a bigger problem, i.e. project failure (Mashali et al. 2023).

There is a need to clearly define and determine success factors (factors leading to project success/failure) and success criteria (measures for evaluating a project as a success or failure) for construction projects to make project success measurement possible. Therefore, the first objective of this research is to extend the project-oriented model by compiling an all-inclusive set of project success factors and criteria and clustering them to evaluate project success in the construction industry. This study encompasses both efficiency- and effectiveness-oriented measures to precisely evaluate project success. Moreover, creating a decision support system to forecast the success of a construction project at its early stages or even before initiating the project would potentially save time and effort by providing an opportunity to highlight and resolve potential causes of problems. The second objective of this study is, therefore, to propose a methodology based on artificial neural networks to forecast the success of medium and large construction projects. To achieve this objective, our research develops an adaptive neuro-fuzzy inference system (ANFIS) because of its capability to effectively handle implicit and explicit knowledge (Sarkar et al. 2023). The adoption of ANFIS allows for the modelling of experts' imprecise knowledge regarding project success factors and criteria using fuzzy expressions. This enables optimized learning for nonlinear and dynamic problems, resulting in more accurate forecasts. Therefore, the developed ANFIS model has the

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potential to help sponsors and project stakeholders forecast the level of project success.

Specifically, this research seeks to answer the following questions:

1. What project success factors and criteria can managers and decision makers use to forecast the success of medium and large construction projects?
2. What is the architecture of the adaptive neuro-fuzzy inference system (ANFIS) to forecast the success of medium and large construction projects?

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on project success. Section 3 explains the Delphi technique and develops an ANFIS to predict the success of construction projects. The Australian and New Zealand construction industry is analyzed using the developed ANFIS in section 4 and section 5 concludes the paper.

Literature REVIEW

Success criteria for construction projects

The concept of project success is very complex and more likely to vary according to people's perceptions (Jugdev and Müller 2005). "The only thing that is certain in project management is that success is an ambiguous, inclusive, and multidimensional concept whose definition is bound to a specific context" (Ika 2009). Despite all complexities, project success is an "evergreen" theme at the heart of any project and many scholars are frequently investigating it (Radujković et al. 2021). In order to be successful, projects must not only show high operational efficiency but also, must be tactically and strategically successful (Samset and Volden 2016). Operational efficiency deals with the project outputs in terms of schedule, cost, and quality and how well the project has transformed the inputs into the outputs. Tactical effectiveness concerns the accomplishment of the predefined outcomes. Strategic relevance shows whether the final deliverables of the project are needed by society or not. It is measured in terms of broad national political priorities, preferences of stakeholders and conflicts of interests among them (Volden 2018; Welde 2018). Given the high variety of success criteria, it is possible that one typical project is considered successful in terms of some specific criteria and is viewed as less/not successful in terms of other criteria (Chen et al. 2012; Mohsen Alawag et al. 2023). Therefore, measuring and achieving project success is very difficult in the construction industry (Alashwal et al. 2017; Zaman et al. 2023).

A clear understanding of project success demands a thorough knowledge of success factors and success criteria. Several studies have identified success factors and success criteria and proposed various approaches to evaluate project success over the last few decades (Radujković et al. 2021). Literature shows that an interdependent and holistic set of project success factors and project success criteria are the prerequisite for measuring project success (Rana et al. 2015). Nonetheless, the literature lacks a consensus on how to define project success, what are the constituents of project success, and what factors are critical to achieving project success in the construction industry (Aboseif and Hanna 2023; Amies et al. 2023; Zaman et al. 2023). To overcome the shortcomings of previous approaches in the thorough evaluation of project success, this study develops a set of sophisticated measurements that allow these broad parameters to take effect. Since it is critical to determine which success criteria should be used to evaluate construction projects, this research is advancing knowledge by developing a more nuanced perspective/framework to project success evaluation.

Success factors of construction projects

Critical success factors (CSFs) in construction projects are specific factors whose presence or absence has a significant influence on project success (Alzahrani and Emsley 2013; Fathi and Shrestha 2023). Knowing critical success factors for construction projects is found to improve management strategies through better risk management processes and better utilization of resources toward the project objectives (Liang et al. 2023). Objectives of a project should denote the establishment of the expected long-term goals and their impacts should last beyond the immediate outputs of the project (Shenhar and Holzmann 2017). Strategic objectives of a construction project act as a strong link to authentic leadership where project managers understand how to encourage and motivate the project team to effectively perform their activities to achieve project objectives (Wang et al. 2023). Project managers directly influence project success by implementing project management standards and practices to plan, execute, monitor and control project activities which enhance project efficiency and effectiveness (Zaman et al. 2023). Their significant contribution to project success is evident through supporting the project team and helping them to realise their full potential, making strategic decisions, communicating with stakeholders and effectively managing their expectations, and more importantly, practising transformational leadership to manage team members (Imam 2021) which leads to higher motivation of team members, successful implementation of changes and adaptation to them, and more innovations (Zaman 2020). However, there are a vast number of factors, which leads to time and cost overruns in construction projects, such as contractors, that are beyond the control of a project manager (Magkaka et al. 2023). Along with the indispensable role of project stakeholders in the success of construction projects, procurement practices and the contracting process play an important role in project success because they facilitate the design and construction of the project especially when it is modular (Wuni and Shen 2022). A competitive and transparent procurement process substantially reduces corruption and unethical practices in the project and contributes to project success (Wang et al. 2023). The construction industry is one of the top three industries with the highest carbon emission and energy use globally (Ma et al. 2017). Therefore, to minimise the negative impacts on public health and welfare, and avoid environmental pollution, project managers need to take into account sustainability matters (Kiani Mavi and Standing 2018; Sawadogo et al. 2022; Toriola-Coker et al. 2023). The environmental dimension of sustainability has gained more importance, compared to the social and economic dimensions, in the success of construction projects (Phung et al. 2023).

As technically skilled and experienced team members improve the competitive advantage of the project and help it in accomplishing its goals, the project team is of fundamental importance for project success (Rasool et al. 2022). Appropriate knowledge sharing among team members and innovation positively contribute to project success by bringing the hard, "things-related", and soft, "people-related" factors together in the projects (Agbejule and Lehtineva 2022; Zaman et al. 2023). This implies that the capability of project managers and project team are major determinants in achieving project success (Gudienė et al. 2013; Kiani Mavi et al. 2021; Waseem et al. 2022).

2.3. Applications of ANFIS in the construction industry

The ANFIS algorithm leverages the advantages of both artificial neural networks (ANN) and fuzzy systems while overcoming their limitations. By combining the two techniques, ANFIS, as a hybrid tool, provides an effective, rapid, and highly predictive solution for addressing complex problems that are nonlinear, uncertain, and dynamic (Jain et al. 2022; Yevu et al. 2022). Yevu et al. (2022) employed ANFIS to analyze the influence of 15 barriers to implementing electronic procurement technology (EPT) in the construction industry. They found that barriers related to human factors, technological risks, and government factors have a higher influence on EPT implementation compared to financial and industry growth barriers. To help decision-makers in construction management, Faraji (2021) identified 25 independent variables (CSFs) within two categories of controllable and uncontrollable dynamics. He then developed an ANFIS model to forecast project performance in the downstream sector of the petroleum industry. Given the importance of green lean six sigma projects for sustainable development, Ershadi et al. (2021) modelled the influence of 28 inputs (CSFs) on 9 outputs (success criteria) using ANFIS in order to forecast their performance. They implied that the technology readiness of the organizations plays a significant role in selecting process improvement projects. Moghayedi and Windapo (2019) compiled a set of 77 factors that influence the timely completion of highway construction projects and developed an ANFIS system to predict the time performance of those projects. They took a risk management perspective for this purpose, however, did not identify the most influential factors that lead to the on-time completion of projects. This technique has been successfully implemented to forecast health and safety risks (Jahangiri et al. 2019; Soualhi et al. 2019; Sadeghi et al. 2020), the productivity of human resources (Shahtaheri et al. 2015; Golnaraghi et al. 2019) and construction operations (Mirahadi and Zayed 2016), and construction waste in the context of circular economy (Akinade and Oyedele 2019).

Research gap

Table 1 summarizes the main features of the current study and compares it with recent studies that have investigated project success using statistical or other techniques.

It shows that researchers have utilized two major categories to analyze project success. Statistical studies have mostly employed structural equation modelling (SEM) to test the significance of relations between project success and variables that lead to it. However, the other group of researchers have used ANFIS or combination of ANFIS with metaheuristics methods such as genetic algorithm to forecast a dependent variable such change order management (COM) performance, and electronic procurement technology (EPT) usage. Given the complexity and multidimensionality of construction projects, there is a clear gap in the comprehensive identification of critical success factors and criteria. As Table 1 indicates, one of the major drawbacks of current literature in construction project management is the lack of knowledge about the factors that lead to project success or failure and evaluating project success in terms of a comprehensive set of criteria (Nguyen et al. 2018; Aboseif and Hanna 2023). On the other hand, the differences among projects make it very difficult to evaluate the success of all projects with the common criteria of time, cost, and quality (Mashwama et al. 2017). Therefore, the success of construction projects should be investigated from a more holistic perspective than the conventional indices in terms of budget, schedule and specifications (scope) or one specific aspect of success like stakeholder satisfaction; to give a common understanding of project success measurements (Chen et al. 2012; Amies et al. 2023; Fathi and Shrestha 2023). The performance level of construction projects continually varies because of (1) the multiple interacting factors that influence project performance, (2) the probabilistic and deterministic nature of influencing factors/independent variables, and (3) the changing and dynamic behaviour of influencing factors over time (Moghayedi and Windapo 2019; Gerami Seresht and Fayek 2020). Therefore, measuring project performance and forecasting it accurately is complex for construction practitioners, which necessitates effective tools and techniques for construction modelling (Tiruneh et al. 2020). ANFIS is capable of handling multiple inputs and multiple outputs, with complex linear and nonlinear relationships, it can therefore be successfully employed to forecast outcomes in the construction industry (Tiruneh and Fayek 2022). Accurate measurement of project success is a necessary component of the solution to the poor performance of construction projects. The application of ANFIS in forecasting project success in the construction industry is rare, therefore, this research seizes this great opportunity to employ ANFIS in determining the interrelationships among critical success factors and critical success criteria of construction projects to forecast project success. When contractors, sponsors, owners, and project managers understand that a project is more/less successful than previous similar projects, they then can address the weaknesses and improve the strengths to enhance the success of their own project in terms of project efficiency, e.g. schedule, budget, scope, quality, and project effectiveness, e.g. business success, and stakeholder satisfaction. Therefore, measuring and managing the success of medium and large construction projects are critically important for all project stakeholders, the public, and the nation to support national growth and development.

Research methodology

The second objective of this research is to develop an ANFIS system to forecast project success. This is achieved through two stages, i.e. a Delphi study to identify the project success factors and success criteria and develop the ANFIS system. The integration of Delphi and ANFIS provides multiple advantages to this study. The Delphi study uses a community of experts to screen and choose the highly important project success factors and criteria for medium and large construction projects. Employing purposive sampling to compose the community of experts ensures that the resulting project success factors and criteria effectively measure project success (Moghimi et al. 2022). This not only enhances the reliability and content validity of the survey used for ANFIS but also improves its forecasting capability by decreasing the complexity and multiplicity of rules in the developed ANFIS through removing unnecessary input and output variables. The application of the ANFIS model provides a clear understanding of project success and the conditions that lead to it. Employing a structured and formal research design in addition to concentrating on a relatively large sample of respondents helps measure the project success more accurately and employ the developed framework as a tool to forecast the success of future projects.

Table 1. Comparison of the current study with the selected recent studies about project success.

Author(s)	Independent (I); Mediating (M); and Dependent (D) Variables	Project Success Factors (F) and Criteria (C)	Research Methodology
(Aboseif and Hanna 2023)		C: Schedule, Cost, Communication, Quality	Classification and regression tree (CART)
(Yevu et al. 2022)		F: Human, Technological risk, Government, Industry growth, and Financial factors; C: Electronic procurement technology (EPT) usage	Adaptive neuro-fuzzy inference system (ANFIS)
(Tiruneh and Fayek 2022)		F: 19 factors including Staff Development, Project Safety Management, Project Procurement Management, Communications C: 7 organizational competencies (Organizational performance, Employee satisfaction, Customer satisfaction, Competitiveness, Quality of work, Safety performance, Effectiveness of planning).	Genetic algorithm (GA) with a multi-output adaptive neuro-fuzzy inference system (MANFIS)
(Naji et al. 2022)		F: 49 Change Order Management (COM) performance factors classified in seven groups (Design management, Quality management, Documentation management, Financial management, Dispute resolution management, Communication and relationship management, Procurement management) C: Change Order Management (COM) Performance	Adaptive neuro-fuzzy inference system (ANFIS)
(Faraji 2021)		F: 25 factors including project delivery system, Financing methods, and construction complexity C: Project performance (Project progress, Resource consumption)	Adaptive neuro-fuzzy inference system (ANFIS)
(Zaman et al. 2023)	I: Toxic leadership; M: Project team member's silence (PTMS) D: Project success (Management, Ownership, Investment)		Covariance-based structural equation modelling (CB-SEM)
(Waseem et al. 2022)	I: Project governance; M: Organizational support, Project team cohesion; D: Project success		Structural equation modelling (SEM)
(Sawadogo et al. 2022)	I: Sustainability management M: Social skills, Political Skills D: Project success		Structural equation modelling (SEM)
(Rasool et al. 2022)	I: Communication, Team, technical, Environmental M: Organizational support D: Project success (Time, Cost, Quality, Stakeholder satisfaction)		Structural equation modelling (SEM)
(Phung et al. 2023)	I: Sustainable project management (5 variables); D: Sustainable project success (environmental, social, economic, project performance and stakeholder satisfaction)		Structural equation modelling (SEM)
(Fathi and Shrestha 2023)	I: 12 risk factors including regulatory, construction, and operation risks; and 10 success factors including collaboration between public and private parties, experience, and established guidelines		Delphi + Intraclass correlation coefficient (ICC)
Current study		F: 53 success factors classified into 9 groups (Project characteristics, Project team, Project manager, Project organization, Project stakeholders, External environment, Sustainability, Contractor, and Procurement process) C: 19 success criteria classified into five groups (Project efficiency, Business success, Impact on end-users, Impact on stakeholders, and Impact on the project team)	Delphi + Adaptive neuro-fuzzy inference system (ANFIS) + compared with other machine learning techniques (Logistics Regression, Decision Tree, Random Forest, and Support Vector Machine)

Delphi method

The Delphi method is widely used in business and management research to identify important factors/issues for making well-informed managerial decisions (Okoli and Pawlowski 2004; Wiewiora et al. 2016). The Delphi technique has been used to identify benefits, risks, technical specifications, critical success factors and criteria in the construction industry (Cheng and Lu 2015; Chung et al. 2021). Since Delphi is an iterative structured method to solicit information from experts (Diamond et al. 2014), reaching a consensus on the research topic when several current and potential dimensions of it exist, is of paramount importance (Olawumi and Chan 2018; Lei et al. 2023). After conducting every round, participating experts receive the cumulative findings of all participants, then they are provided with an opportunity to re-evaluate and revise their previous responses (Wong and Kuan 2014). If performed with high rigour, a Delphi survey enhances the confidence of researchers in extending knowledge by eliciting the consensus of experts instead of individual opinions and then by proposing new perspectives (Rosario Michel et al. 2023).

3.2. Architecture of ANFIS

Learning from the training data samples, ANFIS generates fuzzy rules in the "If-Then" format to make a fuzzy inference system (FIS) (Yadegaridehkordi et al. 2018). Those rules are fundamental to predicting/forecasting the dependent variable. When there are non-linear relations among independent variables that cause a non-linear behaviour for the dependent variable, ANFIS works extremely well to forecast the dependent variable (Mostafaei 2018). A typical ANFIS architecture with Takagi-Sugeno fuzzy inference system has five layers as shown in Figure 1. This figure shows two input variables and one output variable. The relations between the input and output variables are represented in the form of If-Then fuzzy rules (Golafshani et al. 2020), for example;

$$\textit{If } x \textit{ is } A_1 \textit{ and } y \textit{ is } B_1, \textit{ then } f_1 = p_1x + q_1y + r_1 \tag{1}$$

where p, q, r are the output parameters.

Different layers of ANFIS are described as follows (Akinade and Oyedele 2019; Elbaz et al. 2020; Golafshani et al. 2020; Naji et al. 2022):

Layer 1 (Fuzzification): It determines the membership functions of the input variables. The fuzzy rule-base is specified in this layer, too. The output of each node is calculated as Equation (2):

$$O_i^1 = \mu_{Ai}(x) \tag{2}$$

where A_i is a linguistic variable, O_i^1 is the degree of membership of the fuzzy set A_i, and μ_{Ai} is the membership function of A_i. As mentioned before, when the degree of membership is 1, it shows that x is a full member of the set A_i, and a value of 0 shows that x does not belong to the set A_i. The Gaussian membership function is provided as Equation (3):

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \tag{3}$$

in which a_i and c_i are the premise parameters.

Layer 2 (Multiplication/Implication): The output of this layer is the firing strength of all rules which is the product of all incoming nodes (antecedent connectives);

$$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad i = 1, 2 \tag{4}$$

Layer 3 (Normalization): The output of this layer is the normalised firing strength which is obtained as the ratio of the corresponding firing strength to the sum of all firing strengths, i.e.:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{5}$$

Layer 4 (Defuzzification): The outputs of this layer are the consequent parameters that are calculated with Equation (6):

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i + q_i + r_i)\ , \quad i = 1, 2 \tag{6}$$

where p_i, q_i, r_i are the adjusted consequent parameters.

Layer 5 (Summation): The output of this layer is the summation of all input signals as a single fixed node which is the overall output of the system calculated by Equation (7):

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i = 1, 2 \tag{7}$$

Research process

Figure 2 depicts the flowchart for conducting this research. Phase I has already been conducted in the literature review, so, Phase 2 and Phase 3 are explained step by step.

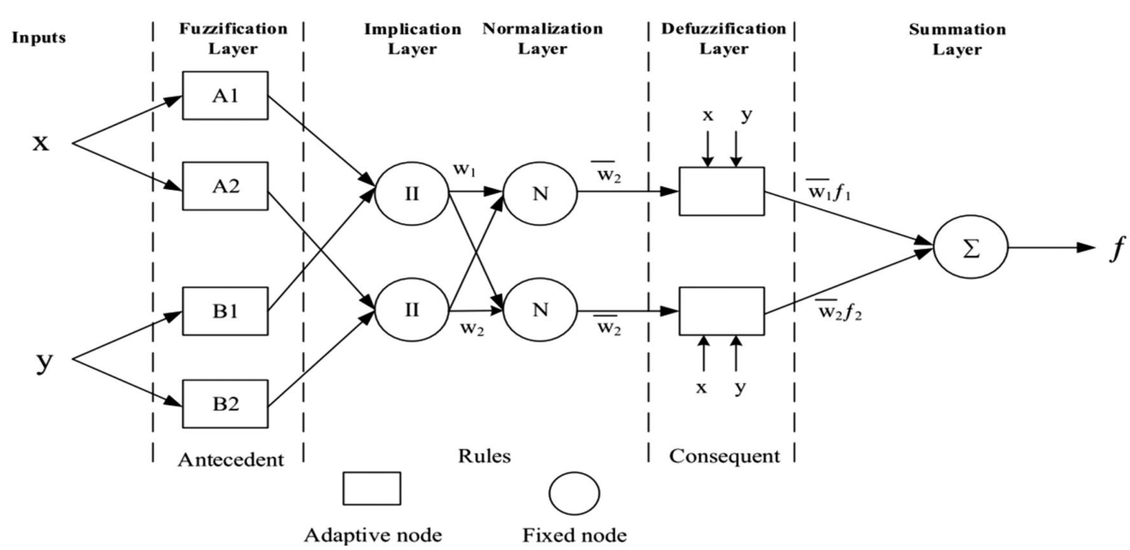


Figure 1. Structure of ANFIS model with two input and one output variables (Elbaz et al. 2020).

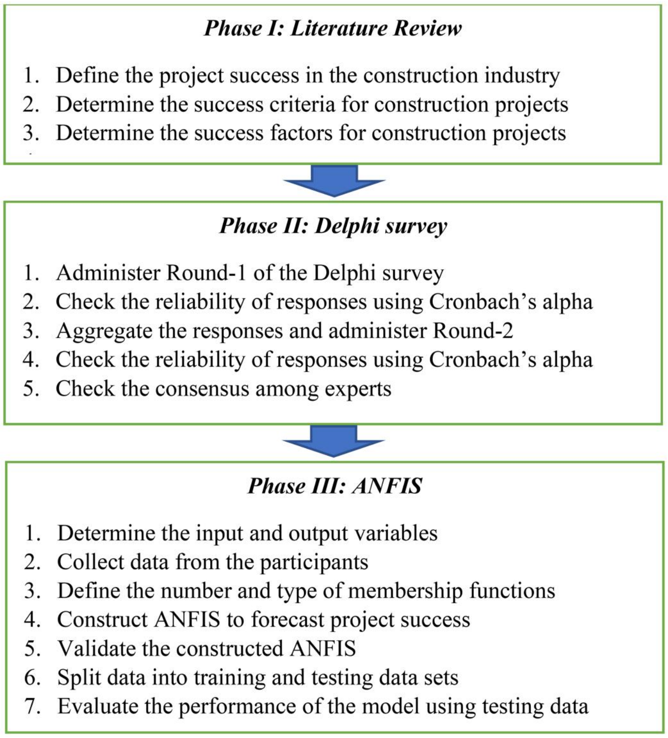


Figure 2. Research process to forecast project success in the construction industry.

Table 2. Demographic characteristics of Delphi participants.

Characteristics	Categories	No. of experts
Gender	Male	9
	Female	2
Experience (year)	5–10	0
	10–15	4
	15–20	4
	20–25	1
	Over 25	2
Job Title	Project Manager	5
	Senior Project Manager	4
	Project Director	1
	Project and Program Director	1

Phase II: Delphi process

Given the characteristics of the Delphi method, it is suitable for this study in determining the most important/common project success factors and success criteria in the construction industry. In this study, we developed an anonymous online Qualtrics survey adopting a five-point Likert scale to measure the importance of project success factors and criteria for medium and large construction projects, including 1-Very Low, 2-Low, 3-Medium, 4-High, 5-Very High. A survey consisting of 64 project success factors and 27 project success criteria was administered. We invited eleven (11) construction project managers with extensive experience in this area to participate in this research. Table 2 presents the demographic characteristics of experts.

The reliability analysis of Round-1 showed Cronbach alpha of 0.886 and 0.874 for project success factors and success criteria, respectively. The opinions of experts were anonymously summarized in graphs and reported to all participants in Round-2. The participants were asked to affirm or revise their opinions. The Cronbach alpha for reliability analysis of project success factors and success criteria revealed 0.958 and 0.947, respectively. Okoli and Pawlowski (2004) recommend 10–18 experts to form a Delphi paned and conduct this technique. They report that reaching an agreement and consensus is the major focus of the Delphi method and it is not dependent on statistical power. This study uses over 80% agreement in the top two points of the five-point Likert scale (4: High and 5: Very High) as the measure of consensus (Putnam et al. 1995; von der Gracht 2012). So, by screening out the less important project success factors (11 factors) and success criteria (8 criteria), those indicators that over 80% of the experts sored their importance as high and very high, were selected for inclusion in the ANFIS system.

The plethora of project success criteria have been assembled into Table 3 *(see* Table S.1 *in the supplementary materials for the relevant sources)*, which shows the project success criteria along with the dominant success characteristic and the source. The authors have adapted the categorization scheme based on the literature review.

A review of the construction project success literature has identified the project success factors shown in Table 4 *(see* Table S.2 *in the supplementary materials for the relevant sources)*. The categorization of CSFs has been adapted based on the literature review.

ANFIS system development

Step 1. Determine the input and output variables: Conducting the literature review and Delphi survey, this research identified 19 project success criteria (see Table 3) and 53 critical success factors (see Table 4).

Step 2. Collect data from the participants: This research focuses on gathering data from managers and experts in the field of construction projects to clarify the interrelations among critical success factors and critical success criteria of those projects. Experts are project managers who have at least five years of experience in the construction industry and have managed at least one medium to large project to completion. An anonymous survey was developed in Qualtircs and administered in Australia and New Zealand. In addition to the eligibility criteria, it contains 72 questions (53 questions for critical success factors, and 19 for critical success criteria), where responses range from 0 to 100. In the case of critical success factors, 0 shows that the given CSF does not influence project success while 100 indicates its very high influence on project success. Project managers were also asked to determine the extent that project success criteria were realized for their recently completed project on a scale from 0 to 100 where 0 shows no success on a certain criterion and 100 shows complete success on a certain criterion. Those projects can be at any level of success from complete failure to complete success. Since ANFIS is a data-driven technique, researchers have performed ANFIS with relatively large samples of data, for example, 81 (Mirzaei et al. 2018), 86 (Shahnazar et al. 2017) and 88 data points (Zhou et al. 2021) to forecast the dependent variable. This study involves gathering data from 142 project managers from the construction industry in Australia and New Zealand. Projects range from commercial and industrial facilities to infrastructure projects such as road construction/expansion.

Step 3. Define the number and type of membership functions: In the real world, the values of decision variables cannot be exactly measured due to the uncertainty and subjectivity of answers provided by the respondents. Fuzzy sets theory employs membership functions (MFs) to express and model the imprecision and uncertainty inherent in the human cognitive processes (Akinade and Oyedele 2019). The degree of membership is a

Table 3. Success criteria of the construction projects.

Success Dimensions	Critical Success Criteria	% of agreement- Round-1 ($n = 11$)	% of agreement- Round-2 ($n = 9$)
Project efficiency	Meeting budget goals	81.82	100.00
	Meeting time goals	100.00	100.00
	Meeting scope and specifications	90.91	100.00
	Technical performance	90.91	88.89
	Efficient project processes	81.82	88.89
	Effective risk management	100.00	88.89
Business success	Value-adding and profitability	90.91	88.89
	Return on investment	81.82	88.89
	Handing over the final construction	100.00	88.89
	Establishing long-term relations and partnerships	81.82	100.00
	Optimised use of available resources	90.91	88.89
Impact on end-users	Quality of construction	81.82	88.89
	Functionality	90.91	100.00
	Customer satisfaction	90.91	88.89
	Fulfilling needs	100.00	100.00
Impact on stakeholders	Stakeholders' satisfaction	90.91	88.89
	Delivering the promised benefits to stakeholders	81.82	100.00
Impact on the project team	Project team satisfaction	81.82	100.00
	Health and safety (in terms of injuries on site)	90.91	100.00

value between zero and one. Pedrycz and Gomide (2007) point out that fuzzy MFs are effectively used to transform the Likert scale responses to fuzzy numbers. Gaussian MFs are preferred over other MFs because they construct a more reliable evaluation system, ensure accurate expression of the input/output relationship, and require a lower number of rules (Gerami Seresht and Fayek 2020; Naji et al. 2022). The development of ANFIS systems and analysis of their performance have been conducted using MATLAB R2022b. In this research, we used five Gaussian MFs according to the 5-point Likert scale which their degree of membership varies between zero and one. ANFIS automatically develops Gaussian MFs as Very Low ($\sigma = 10.62,\ \mu = 0$), Low ($\sigma = 10.62,\ \mu = 25$), Medium ($\sigma = 10.62,\ \mu = 50$), High ($\sigma = 10.62,\ \mu = 75$) and Very High ($\sigma = 10.62,\ \mu = 100$). Figure 3 illustrates the Gaussian MFs for project characteristics.

Step 4. Construct ANFIS to forecast project success: Figure 4 illustrates the structure of the developed ANFIS which includes 9 input variables (project success factors) and five output variables (project success criteria).

The arithmetic average of all success factors or success criteria in each group is used as the proxy for that specific success factor or criterion. For example, the first input variable 'Project Characteristics' involves four success factors, i.e. clear realistic objectives, project size and level of complexity, minimal scope change, and cost-efficient work practices, which their average is considered as the value of this input variable to forecast the outputs. This study develops seven fuzzy inference systems based on the desired outputs. ANFIS 1 is used to forecast 'project efficiency'. ANFIS 2 – ANFIS 5 are dedicated to separately forecast the effectiveness-related success criteria, i.e. business success, impacts on end-users, impacts on stakeholders, and impacts on the project team, respectively. The average of four effectiveness-related success criteria is called 'project effectiveness' which is predicted using ANFIS 6. Finally, the output variable for ANFIS 7 is 'project success' which is the arithmetic average of all success criteria and measures the overall success of a construction project. So, this system is capable of forecasting project success from efficiency and effectiveness angles both separately and altogether.

Step 5. Validate the constructed ANFIS: To validate the proposed ANFIS system, this research performs (1) structural validations, (2) behavioural validation, and (3) validation by a case study (Khalef and El-Adaway 2021; Khan et al. 2021; Naji et al. 2022).

Structural validation qualitatively ensures the dimensional consistency of the model by determining the project success factors and criteria (Naji et al. 2022). All the success factors and criteria have been identified and clustered through a comprehensive literature review and confirmed by academic and industry experts (3 academics and 11 construction project managers).

To perform a *behavioural validation* on the model and to check whether or not it appropriately forecasts project success, this research conducts k-fold cross-validation (Khan et al. 2021). In this approach, the available data is randomly divided into k groups or folds (of approximately the same size). This approach trains and tests the proposed ANFIS model k times, each time, k -1 folds are used for training, whereas the remaining one fold is used for testing it. Therefore, each observation is used k -1 times for training and once for testing the proposed ANFIS. The accuracy measures are computed for each round and finally, their average represents the accuracy of the model (James et al. 2021). Research shows that k-fold cross-validation with $k = 10$ accurately measures the performance of the statistical learning models (James et al. 2021; Khalef and El-Adaway 2021; Khan et al. 2021; Naji et al. 2022). This technique is very effective in verifying the validity of the proposed ANFIS because it has the opportunity to test/check its performance using all available data (Naji et al. 2022). The results of the k -fold cross-validation have been provided in Section 4.1.

To validate the practicality of the proposed ANFIS, we implemented it on a real construction project in Western Australia (WA). This project one is a large-sized facility construction with an initial approved budget of over $210 million. This project has been completed in 2022 by a WA-based contractor. The results have been reported in Section 4.2.

Step 6. Split data into training and testing data sets. We initially collected 174 responses from project managers. To validate the data, we pre-processed them to screen surveys with missing values, incorrect responses, and outliers (Singh et al. 2016). The pre-processing led to removing 32 unworkable survey responses. All remaining 142 sets of data are randomly placed in rows to ensure that there is no preference in selecting the training and testing datasets. Splitting data is performed in terms of the availability of data. While many studies used 80% of data to train the developed ANFIS and 20% of data to test the performance of the model (Elbaz et al. 2020; Faraji 2021), the most commonly used ratio for training and testing data is 70% and 30%, respectively (Tiruneh and Fayek 2022). Therefore, this research splits data

Table 4. Project success factors in the construction industry.

Categories of project success factors	Critical Success Factors	% of agreement-Round-1 ($n = 11$)	% of agreement-Round-2 ($n = 9$)
Project characteristics	1. Clear realistic objectives	81.82	88.89
	2. Project size and level of complexity	81.81	88.89
	3. Minimal scope change	90.91	88.89
	4. Cost-efficient work practices	81.81	100.00
Project team	5. Troubleshooting skills of project team members	100.00	100.00
	6. Trust and confidence among team members	100.00	100.00
	7. Effective project risk management	100.00	100.00
	8. Effective project planning and scheduling methods	100.00	100.00
	9. Competent/ motivated and well-integrated team	81.81	88.89
	10. Commitment of the project team	100.00	100.00
	11. Effective/ adequate/ clear information sharing and communication with major stakeholders	90.91	88.89
	12. Delegation of work/ authority/ responsibility	100.00	100.00
Project manager	13. Competent project manager	100.00	100.00
	14. Power of the project manager	100.00	100.00
	15. Project managers' emotional intelligence	90.91	100.00
	16. Knowledge and adoption of project management processes, tools and techniques	100.00	100.00
	17. Project manager's construction experience	100.00	100.00
	18. Project manager's leadership competency and style	100.00	100.00
Project organization	19. Resource availability and sufficiency	90.91	100.00
	20. Commitment of senior management	90.91	88.89
	21. Monitoring project performance	100.00	100.00
	22. Positive relationship with stakeholders	81.82	88.89
	23. In-depth technical understanding of the project at outset	90.91	100.00
	24. Supportive culture	81.82	88.89
	25. Robust progress monitoring systems	81.82	100.00
	26. Effective change management	81.82	88.89
	27. Supportive organizational environment	81.82	100.00
	28. Health and safety training/ programs/ inspection	90.91	100.00
Project stakeholders	29. Managed stakeholder expectations	81.82	100.00
	30. Stakeholders'/clients' support and responsiveness	81.82	88.89
	31. Clear priorities and goals of the stakeholders	90.91	100.00
	32. Mutual trust among project stakeholders	81.82	88.89
External environment	33. Ability to comply with end-user constraints	81.82	88.89
	34. Knowledge of environmental concerns and relevant regulations	81.82	100.00
	35. Availability of relevant human resources	90.91	88.89
	36. Address relevant government regulations and laws	81.82	88.89
Sustainability	37. Energy consumption / utilizing clean and renewable energies	81.82	88.89
	38. Water conservation	81.82	88.89
	39. Construction cost	90.91	88.89
	40. Community involvement	81.82	88.89
	41. Environmental protection through effective waste management	81.82	88.89
Contractor	42. Effective sourcing of contractors	90.91	100.00
	43. Balance of inhouse and sub-contracting activities	81.82	100.00
	44. Contractor's competencies (managerial and technical) and commitment	100.00	100.00
	45. Appropriate contract clauses for dispute resolution	81.82	88.89
	46. Type and size of past projects completed by the contractor	90.91	88.89
	47. Size, reputation, and age of the contractor	81.82	88.89
	48. Financial stability of the contractor	100.00	100.00
	49. The safety performance of the contractor	100.00	100.00
	50. Availability and utilization of modern and automated technologies for construction work	81.82	100.00
Procurement process	51. Competitive procurement processes	100.00	88.89
	52. Effective tendering method	100.00	88.89
	53. Transparency in the procurement process	90.91	100.00

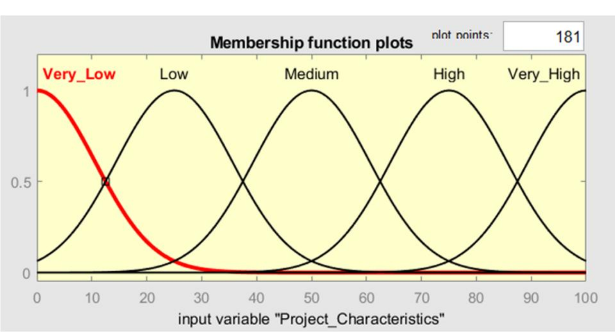


Figure 3. Membership functions of the input variable 'project characteristics'.

into training (70%) and testing (30%). The proposed ANFIS is trained using the training data set and its applicability is tested using the testing data set. The results have been further discussed in Section 4.2.

Step 7. Evaluate the performance of the model using testing data: Evaluating the performance of any statistical learning method including ANFIS requires a series of forecasting accuracy indexes. The validity of developed ANFIS is examined using forecasting accuracy measures such as coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute per cent error (MAPE) (Azad et al. 2018; Mostafaei 2018; Olatunji et al. 2022), relative root mean square

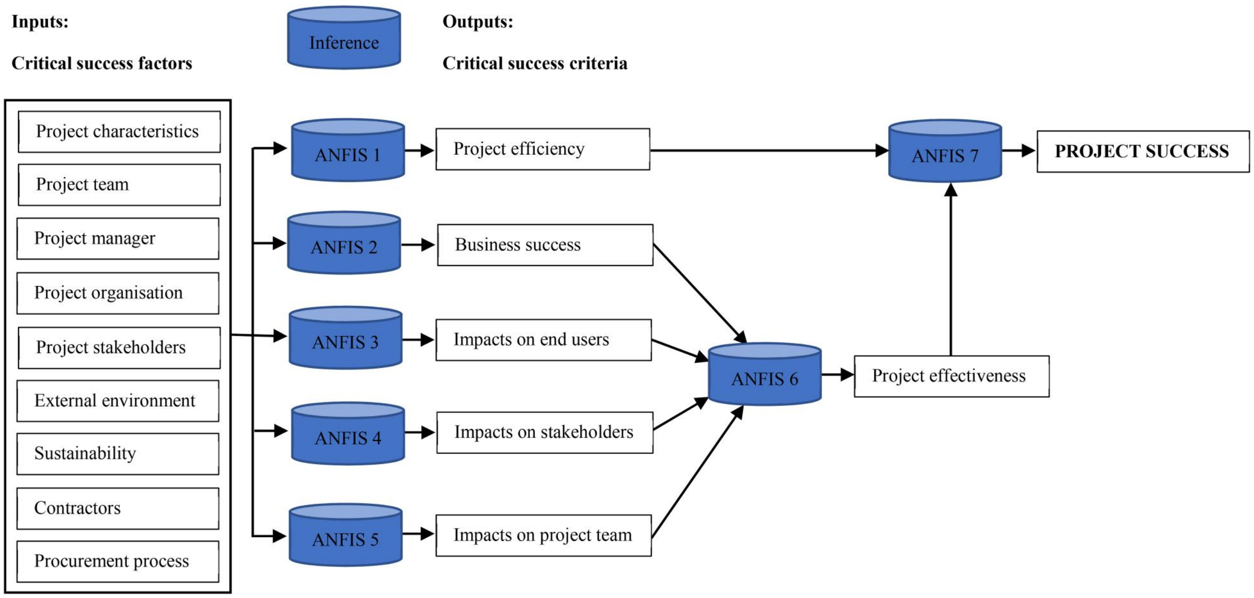


Figure 4. ANFIS model architecture for project success in the construction industry.

error (RRMSE), and performance index (PI) (Gandomi and Roke 2015; Jalal et al. 2021; Naji et al. 2022). These statistical measures are obtained using Eqs. (8)-(13):

$$R = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \times \sqrt{n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}} \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \tag{10}$$

$$RRMSE = \frac{1}{|\overline{x}|}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{11}$$

$$I = \frac{RRMSE}{1 + R} \tag{12}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - y_i|}{x_i} \times 100\% \tag{13}$$

where n is the number of observations (sample size), x_i are the observed outputs found from the survey, $\overline{x}$ is the average of the observed outputs, and y_i are the forecast outputs predicted by the developed ANFIS. The smaller values of RMSE, MAE, RRMSE, MAE, and PI, whereas the higher values of R^2 posit the better performance of the forecasting model. The coefficient of correlation (R) determines the linear correlations between the observed and forecasted outputs. $R > 0.8$ indicates a strong relationship between the observed and estimated outputs (Jalal et al. 2021). Because the value of R does not change by multiplication or division of the outputs (Iqbal et al. 2020; Jalal et al. 2021), the coefficient of determination $(0 \leq R^2 \leq 1)$ is employed to assess the proportion of variability in y that can be explained by x. The higher values of R^2 represent a better fit between the observed and predicted outputs (James et al. 2021). The acceptable value of R^2 is dependent on the application, however, $R > 0.8$ and therefore $R^2 > 0.64$ indicate a strong correlation (Gandomi and Roke 2015; Jalal et al. 2021; Naji et al. 2022) in the context of construction engineering and management. The mean squared error (MSE) is the most frequently used measure to judge the quality and performance of a forecasting model because it includes both the variance (the dispersion of the forecasts) and the bias (how far off the average forecasted value is from the observed value) of the estimator (James et al. 2021). To make it easier to understand and explain, the root mean square error (RMSE) is used. Clearly, the lower values of RMSE (zero or close to zero) show a minimal forecasting error and a good fit (Santos et al. 2021; Naji et al. 2022; Oliaye et al. 2023). Notwithstanding, in specific situations where the variances are high, this measure does not guarantee the best performance. As the changes in MAE are linear and more intuitive, it is very helpful when data are smooth and continuous (Jalal et al. 2021; Sarkar et al. 2023). The MAE is obtained as the average of the absolute values of error terms. Mean absolute percentage error (MAPE) is a relative measure that transforms MAE to be presented in percentage units instead of the variable's unit. Similar to MAE and RMSE, the lower values of MAPE ($MAPE \leq 10\%$) represent a better fit (Moghayedi and Windapo 2019). Because RMSE and MAE are scale-dependent, the performance index (PI), a scale-free measure, is used which considers both the correlations and error functions simultaneously where the RRMSE is the relative RMSE. A strongly accurate forecasting model presents $RRMSE \leq 0.1$ *or* 10% (Despotovic et al. 2016). When the performance index is close to zero $(PI \leq 0.2)$, the model performs well and the forecasted outputs are reliable (Gandomi and Roke 2015; Naji et al. 2022).

Results and discussion

This section is dedicated to data analysis and presents the results of training and testing the proposed ANFIS. The findings of the *k*-fold cross-validation procedure are explained, and then the forecasting accuracy measures are presented to verify the validity of the developed ANFIS.

k-fold cross-validation

k-fold cross-validation is implemented to evaluate the behavioural validity of an ANFIS system. This research divided 142 data sets into 10 subsets (eight subsets with 14 and two subsets with 15 observations). We trained the developed ANFIS models using different approaches for generating fuzzy inference systems (FIS) including grid partitioning, FCM clustering, and subtractive clustering. Furthermore, we developed a set of 1847 'If-Then' rules looking at the likely combinations of the input variables. The rules have been developed in two cases: (a) when the membership function of the output is linear, and (b) when the membership function of the output is constant. In both cases, we considered three levels of success-related output, i.e. poor, medium, and significant. The accuracy measures obtained by a 10-fold cross-validation process for ANFIS 7 have been depicted in Tables 5 and 6.

$R^2 = 0.97461$ indicates that 97.461% of variations in project success forecasted by proposed ANFIS with linear membership functions are because of changes in the observed project success. As the critical success factors determine the success of a project, it is inferred that 97.461% of changes in the estimated project success are attributed to changes in project success factors such as clear objectives of the project, support of senior management, competency of the project manager, and transparent procurement processes. $R > 0.8$ (therefore $R^2 > 0.64$) (Gandomi and Roke 2015) is a sign of a good forecasting method that has a high capability to accurately forecast project success. Table 5 reveals that grid partitioning, FCM clustering, and subtractive clustering fail in training data to appropriately forecast project success close to the survey observations. Testing data play a much more important role in confirming the suitability of the forecasting method. Table 6 also reports a very low coefficient of determination for grid partitioning and FCM clustering, 0.05036 and 0.02144 respectively, while that for subtractive clustering is low, 0.56429. In addition, we need to consider dispersion measures such as MAPE, MAE, and RMSE to decide whether a forecasting technique is capable of reliable estimation. For example, $MAPE = 39.04537\%$ pinpoints that project success scores forecasted by grid partitioning are over 39% far off their observed success scores. Previous studies recommend avoiding forecasting methods with $MAPE > 25\%$ while $10\% < MAPE \leq 25\%$ implies an acceptable forecasting method, and $MAPE \leq 10\%$ denotes a very good forecasting technique (Swanson 2015; Moghayedi and Windapo 2019). Therefore, grid partitioning does not provide reliable forecasts while the estimations made by FCM clustering and subtractive clustering are not very good. MAE and RMSE mean that on average how far forecasts are from the observations. For example, $MAE = 18.73143$ highlights that, on average, the difference between the observed project success scores and those scores forecasted by the FCM clustering technique is 18.73143 units. It is worth noting that MAE considers the absolute errors so the differences can occur in both directions (forecasts can be less or more than the observations). Because MAE and RMSE are scale-dependent, RRMSE and PI are used to analyze the accuracy of forecasting methods. These are very effective measures in evaluating forecasting performance as they take into account the variances and biases together. In addition to $PI \leq 0.20$, a good forecasting method should provide $RRMSE \leq 10\%$ (Gandomi and Roke 2015; Jalal et al. 2021). By conducting a k-fold cross-validation procedure, we conclude that the proposed ANFIS with constant membership functions, grid partitioning, FCM clustering, and subtractive clustering are not suitable methods for estimating project success in this research because of their poor performance. Since the proposed ANFIS with linear membership functions meets the requirements of all commonly used forecasting accuracy measures, it outperforms all other FIS generation methods and provides a good fit between the observations and the estimations. Therefore, we make use of it to forecast the success of medium and large construction projects. We repeated this process on all proposed ANFIS systems (ANFIS 1- ANFIS 7) and arrived at the same decision.

Training and testing ANFIS

Now that the proposed ANFIS systems have been validated, this section reports the findings of training and testing them with 70% and 30% of data sets, respectively. It also illustrates the diagram of testing ANFIS 7, as an example. A summary of findings for all ANFIS systems has been provided in Table 7.

This study used 99 (70%) pairs of data to train the ANFIS systems and the remaining 43 (30%) pairs of data to test the developed model to forecast 'project success' and its components. Figure 5 shows the match between the observed 'project success' scores and those forecasted by ANFIS 7 with $RMSE = 2.361$. It means that, on average, the observed 'project success' scores of testing data are 2.361 units different from the 'project success' scores forecasted by ANFIS 7. RMSE is one of the most frequently used error measures for evaluating the quality of fit between the observed (actual) data and forecasting outputs (Dao et al. 2022).

Table 7 shows the accuracy measures for ANFIS 7 in forecasting 'project success'. The difference between the observations and forecasted outputs has also been measured by MAE as the average of absolute errors, 1.188425. The mean absolute percentage error (MAPE) for testing data is $2.57912\% \leq 10\%$ indicating the strong capability of ANFIS 7 in accurately forecasting 'project success'. It denotes that, on average, the forecasted 'project success' scores are 2.57912% away from the observed scores.

Table 5. Performance of FIS generation methods with training data using 10-fold cross-validation - ANFIS 7.

FIS generation method	R^2	MAPE	MAE	RMSE	RRMSE	PI
Proposed rule set (Linear MFs for the output)	1	0.00351	0.00297	0.00498	6.08E-05	3.04E-05
Proposed rule set (Constant MFs for the output)	0.99102	0.01641	0.02413	0.01582	0.00021	0.0001
Grid Partitioning	0.47634	6.32515	2.04531	1.63263	0.02159	0.01277
FCM Clustering	0.14219	13.01274	15.41832	7.64547	0.10113	0.07344
Subtractive Clustering	0.28212	12.44316	10.32244	4.31927	0.05713	0.03731

Table 6. Performance of FIS generation methods with testing data using 10-fold cross-validation - ANFIS 7.

FIS generation method	R^2	MAPE%	MAE	RMSE	RRMSE	PI
Proposed rule set (Linear MFs for the output)	0.97461	2.57912	1.88425	2.361	0.03149	0.01589
Proposed rule set (Constant MFs for the output)	0.71115	8.35014	7.00213	11.2451	0.14874	0.08069
Grid Partitioning	0.05036	39.04537	25.03182	13.14516	0.1768	0.14439
FCM Clustering	0.02144	12.44394	18.73143	71.21067	0.95777	0.83544
Subtractive Clustering	0.56429	11.96437	10.34281	12.39813	0.16548	0.09449

Considering both the correlation between the observations and forecasts and their dispersion, RRMSE and PI are obtained. $RRMSE = 0.03149 \leq 0.1$ and $PI = 0.01589 \leq 0.2$ (Gandomi and Roke 2015; Jalal et al. 2021) confirm the strong validity and reliability of ANFIS 7 in appropriately forecasting 'project success'.

An example of a ANFIS surface for poor, medium, and significant 'project success' is shown in Figure 6(a-c). for example, Figure 6-b reveals that when all inputs take a value of 50, the forecasted 'project success' is 50.0005.

Table 7. Performance of ANFIS 7 in forecasting project success.

Data set	R^2	MAPE%	MAE	RMSE	RRMSE	PI
Training data	1	0.00351	0.00297	0.00498	6.08E-05	3.04E-05
Testing data	0.97461	2.57912	1.88425	2.361	0.03149	0.01589

Using the developed rule-set, i.e. 1847 rules with the linear MFs for the output, the accuracy measures of all project success criteria are obtained both separately and combined (see Tables 8 and 9).

As Table 9 reveals, the coefficient of determination for the overall 'project success' is 0.97461, which means that 97.46% of variations in project success are dependent on the variations in the 9 categories of project success factors, and $1 - R^2 = 0.02539$ or 2.54% of them might be attributed to other factors which have not been included in the model including random changes. As the forecasting accuracy measures for all ANFIS systems meet the acceptance criteria, we conclude that there is a very strong correlation between critical success factors and project success (Cleophas and Zwinderman 2021) which verifies the validity of proposed ANFIS systems. This means that the identified critical

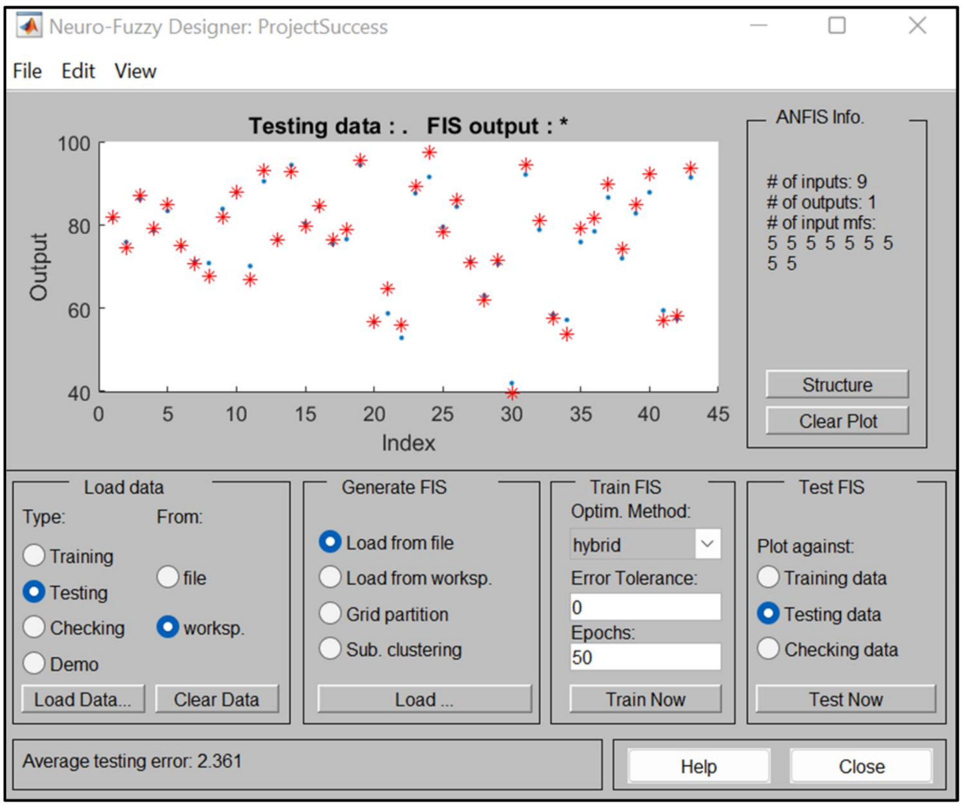
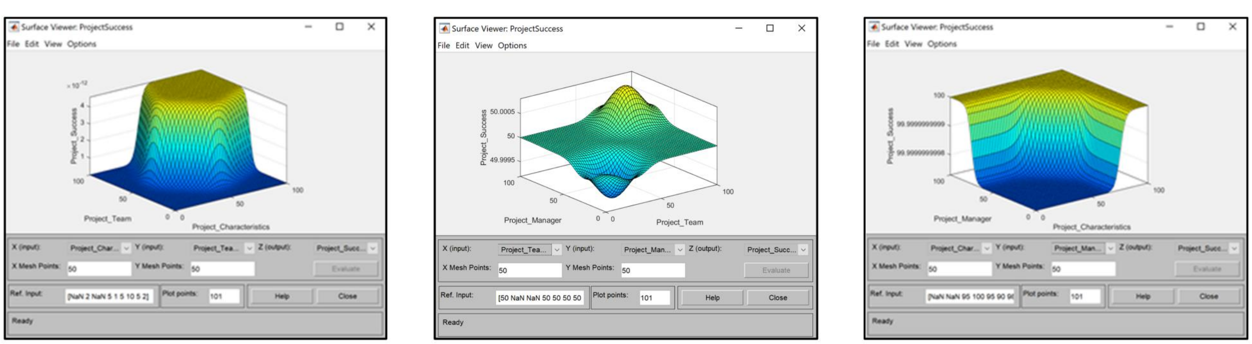


Figure 5. Testing error of the developed ANFIS 7.



(a). Poor project success **(b).** Medium project success **(c).** Significant project success

Figure 6. Forecasted project success for combinations of input variables.

Table 8. Performance of developed ANFIS systems with training data.

Project success criteria	R^2	MAPE%	MAE	RMSE	RRMSE	PI
ANFIS 1: Project efficiency	0.99999	0.00627	0.00562	0.02345	0.00028	0.00014
ANFIS 2: Business success	1	0.0001	0.00008	0.00021	2.56E-06	1.28E-06
ANFIS 3: Impacts on end users	1	0.00013	0.00012	0.00042	5.12E-06	2.56E-06
ANFIS 4: Impacts on stakeholders	1	0.0001	0.00009	0.00034	4.15E-06	2.07E-06
ANFIS 5: Impacts on project team	1	0.00008	0.00007	0.00027	3.29E-06	1.65E-06
ANFIS 6: Project effectiveness	1	0.00011	0.0001	0.00031	3.78E-06	1.89E-06
ANFIS 7: Project success	1	0.00351	0.00297	0.00498	6.08E-05	3.04E-05

Table 9. Performance of developed ANFIS systems with testing data.

Project success criteria	R^2	MAPE%	MAE	RMSE	RRMSE	PI
ANFIS 1: Project efficiency	0.99058	1.6807	1.18685	1.3913	0.01856	0.00930
ANFIS 2: Business success	0.92546	4.93131	3.33231	4.1345	0.05515	0.02811
ANFIS 3: Impacts on end users	0.96372	3.83948	2.57944	3.704	0.04941	0.02493
ANFIS 4: Impacts on stakeholders	0.89491	3.34233	2.77137	5.2875	0.07053	0.03624
ANFIS 5: Impacts on project team	0.75898	6.47085	4.6542	7.0701	0.09431	0.0504
ANFIS 6: Project effectiveness	0.96529	3.12806	2.29517	2.89	0.03855	0.01945
ANFIS 7: Project success	0.97461	2.57912	1.88425	2.361	0.03149	0.01589

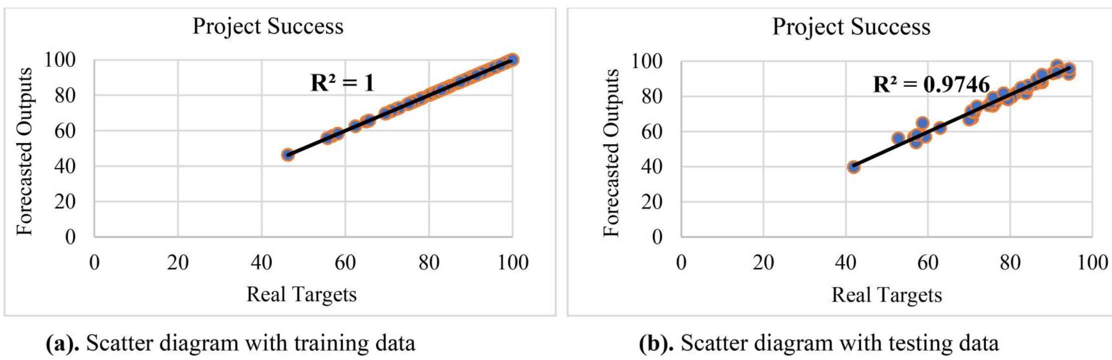


Figure 7. Scatter diagram of the correlation between real (survey) targets and forecasted outputs by ANFIS 7.

success factors can effectively explain the changes in the project success criteria. Figure 7(a–b) graphically depict this concept using the scatter diagram.

Figure 8(a–c) illustrates the capability of the proposed ANFIS 7 in appropriately forecasting project success and shows that how effectively it matches the forecasted outputs with the real survey targets. The error of ANFIS 7 in forecasting project success is shown in Figure 8(b–d).

We entered the data gathered for the real large construction project in Western Australia and found that ANFIS 7 forecasts its success very close to the success score obtained from the survey. The inputs vector is (77, 78, 91, 88, 96, 87, 77, 82, 78) and the survey output is 82.2. Project success is forecasted as 82.4 by ANFIS 7. The absolute percentage error for this observation is 0.24% which is lower than 10% ($MAPE \leq 10\%$) and represents a very good forecasting technique (Swanson 2015; Moghayedi and Windapo 2019) with highly accurate results.

Comparison with other machine learning techniques

We compared the proposed ANFIS system with a few other machine learning techniques to check how capable the proposed system is. The results of training and testing four popular supervised learning techniques (Singh et al. 2016; Makkar et al. 2022) are shown in Table 10.

While the forecasting accuracy measures for these techniques are acceptable, the proposed ANFIS system outperforms all these techniques over all measures with a higher coefficient of determination and lower MAPE, MAE, RMSE, RRMSE, and PI. So, this comparison endorses the reliable performance of the proposed ANFIS system in forecasting project success.

Sensitivity analysis of the project success

To analyze the effects of each success factor on the overall success of medium and large construction projects, a sensitivity analysis is performed. Sensitivity analysis helps determine which factors are more important in predicting project success. To implement sensitivity analysis, one input variable (success factor) is removed from the set of inputs while the output variable (project success) remains unchanged, and ANFIS 7 is run with the same rule structure (Çakıt et al. 2020; Naji et al. 2022). The performance of the revised models encompassing 8 inputs and one output variable is evaluated using RMSE. The factor that its removal results in a higher RMSE, has a higher influence on project success, in other words, it has a higher priority in forecasting project success. The results of the ANFIS sensitivity analysis are represented in Table 11.

Findings show that removing every input variable leads to a higher RMSE measure compared to including all inputs in the model. This means that all inputs significantly contribute to forecasting project success. Removing 'project characteristics leads to the highest RMSE (17.8812), which means that it decreases the accuracy of the forecasting model more than other inputs. Therefore, we assume that this group of success factors have the highest importance in forecasting project success in the construction industry. 'Project team' and 'external environment' are ranked in the second and third places, respectively. 'Sustainability'-related success factors achieved the lowest RMSE.

(a).
(b).
(c).
(d).

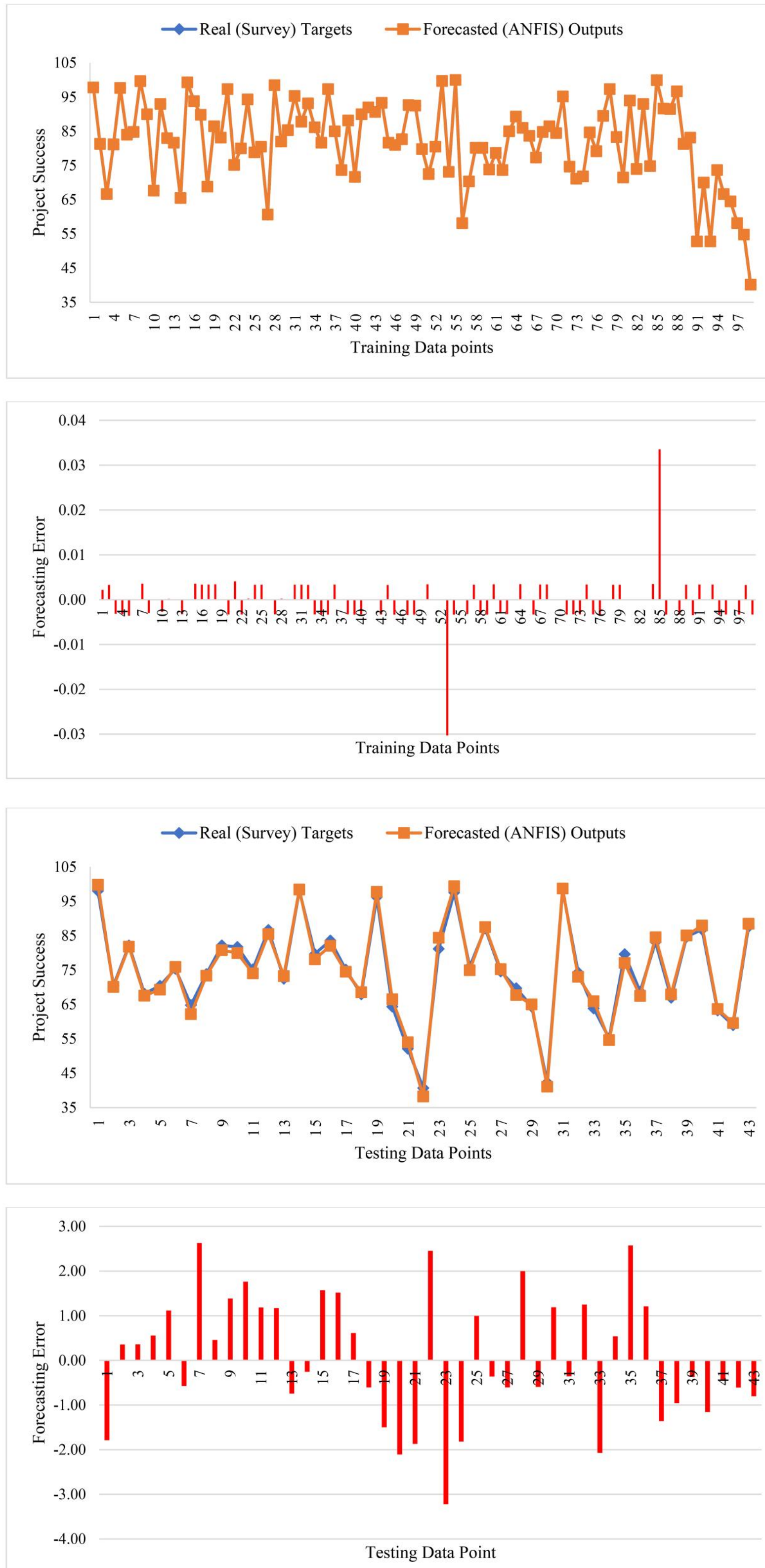


Figure 8. Real targets, forecasted outputs, and forecasting errors of ANFIS 7.

Discussion of the findings

Evaluating project performance becomes more complicated when the success criteria are not established and agreed upon. Project efficiency is commonly used to measure project performance in terms of the iron triangle of schedule, budget, and specifications, whilst project effectiveness criteria consider business success, impacts on end-users, effects on the project team, and establishment of long-term constructive relationship for the future (Bond-Barnard et al. 2018). Due to the need to develop a comprehensive and all-inclusive set of project success criteria,

Table 10. Comparison between ML techniques in forecasting project success.

Forecasting Technique	R^2	MAPE%	MAE	RMSE	RRMSE	PI
Logistics Regression	0.80543	4.6624	3.69596	4.47723	0.05972	0.03147
Decision Tree	0.72778	5.4023	4.24506	5.29575	0.07063	0.03811
Random Forest	0.85439	3.8946	3.09712	3.87317	0.05166	0.02685
Support Vector Machine	0.85041	3.4384	2.68746	3.92577	0.052365	0.02724
Proposed ANFIS 7	**0.97461**	**2.57912**	**1.88425**	**2.361**	**0.03149**	**0.01589**

Table 11. Sensitivity analysis for ANFIS 7.

Removed input	RMSE
N/A	2.361
Project characteristics	17.8812
Project team	11.1605
Project manager	9.1857
Project organization	10.7403
Project stakeholders	7.025
External environment	10.8064
Sustainability	6.6389
Contractor	7.9899
Procurement process	7.6503

following a two-round Delphi method, this research identified 19 project success criteria and classified them into five groups encompassing project efficiency, business success, impacts on end users, impacts on stakeholders, and impacts on the project team (see Table 3). Several antecedents contribute to project success with different levels of importance and influence. As Table 4 illustrates, this research identified 53 critical success factors and clustered them into 9 groups. We developed seven ANFIS systems from which ANFIS 1 estimates project efficiency, and ANFIS 2 – ANFIS 5 are developed to separately predict each component of project effectiveness, i.e. business success, impacts on end-users, impacts on stakeholders, and impacts on the project team, respectively, ANFIS 6 is used to forecast project effectiveness, and ANFIS 7 forecasts the overall project success. Table 9 shows that all developed adaptive neuro-fuzzy inference systems are accurately forecasting the expected outputs ($R > 0.8$, $\mathrm{MAPE} \leq 10\%$, $\mathrm{RRMSE} \leq 0.1$, $\mathrm{PI} \leq 0.2$). ANFIS 7, which is dedicated to forecast the overall project success, provides highly accurate estimations of project success because of its very low RRMSE (0.03149) and PI (0.01589) and very high coefficient of determination (0.97461). This implies that the identified critical success factors are strongly linked to the identified project success criteria and ANFIS 7 is very capable of understanding their complex relations, learning them, and imitating those relations in forecasting the success of construction projects. This concept has been depicted in Figure 7(a-b). The regression line shows the forecasted output (project success in the case of ANFIS 7). As many observations positioned around the regression line, it means that there is not any significant difference between the observations and the forecasted output with ANFIS systems. So, the proposed ANFIS systems can be effectively used by practitioners for evaluating project performance. ANFIS 5 which forecasts impacts on the project team, has the highest RRMSE (0.09431) and PI (0.0504) and the lowest coefficient of determination (0.75898). While this system appropriately infers the impacts of critical success factors on project team and their satisfaction, there might be some other factors that their influences are not easily measured. For example, teamwork in project settings refers to communication, i.e. information sharing, coordination of activities among team members, balanced utilization of team members' knowledge and expertise to contribute to the project objectives, mutual support between team members, putting effort into assigned activities, encouraging cohesion and unity among team members, and ensuring the high quality of project tasks (Hoegl and Gemuenden 2001).

Table 11 displays important insights about the role of the identified critical success factors by determining the changes in the capability of the proposed ANFIS 7 in forecasting overall project success. The group of project characteristics includes four critical success factors, i.e. clear realistic objectives, project size and level of complexity, minimal scope change, and cost-efficient work practices, that have been identified by ANFIS 7 as the most crucial because their removal adds more to the forecasting error ($\mathrm{RMSE} = 17.8812$). Clearly, medium and large construction projects are large in size and typically complex because of their nature, in which multiple parties with different interests work collectively to perform the project (Ahmed and Jawad 2022). This research also shows the high impact of the project team on project success. Medium and large construction projects are often managed and closely monitored by a senior management team (Wang et al. 2023). This research confirms that the objectives of the project should be clearly defined at the early stages of the project in a way that they are realistic and achievable.

The rate of failure or premature termination in construction projects is high which can partially be attributed to scope creep because of higher complexity (Ahmed and Jawad 2022). One approach to developing realistic and achievable project objectives given its size, complexity, available resources, and other constraints, is to prepare a detailed and well-structured responsibility matrix which effectively links to the objectives of the project and that the project team members agree with that, contributes to project success (Wang et al. 2023). Our findings further confirm that project managers and teams should deeply understand the dynamics of project management practices in order to meet the varying expectations of project stakeholders.

Table 11 shows that removing the external environment and project organization from the set of input variables results in a high RMSE scores, 10.8064 and 10.7403 respectively. Factors related to the external environment are typically external factors that are beyond project team control such as government regulations, environmental legislations, and constraints imposed by the customers (Wang et al. 2023). As outlined by Maghsoodi and Khalilzadeh (2018), effective and supportive regulatory systems such as legal security platforms, financial policies and procedures, project supervision mechanisms, and stakeholders involvement pave the way for the successful implementation of a project. In addition, a socially- and culturally-constructive environment is necessary for good governance in the project because it helps in realising social sustainability (Chen et al. 2022). Furthermore, management support in medium and large construction projects involves organising and directing many multidisciplinary participants who collaborate as a team to achieve the established project objectives using advanced management techniques for problem-solving because multidisciplinary teams retain extensive skills and expertise to solve problems related to project schedule, quality, and risk management (Chen et al. 2022). The senior management team and project managers are the major communication conduits with the external environment and project stakeholders. Gaining the support of stakeholders and complying with the external regulations and rules are necessary for project success (Rasool et al. 2022), especially efficiency-related criteria of time, cost and quality. On the other hand, the modern world necessitates the use of technology in performing projects. Therefore, the technical capacities of the project organization such as information technology (IT) infrastructures and capabilities significantly contribute to project performance and improve the competitiveness of the organization (Akram et al. 2018).

Research shows that disputes among clients and contractors inversely influence stakeholders' satisfaction and project success (Mangu et al. 2021). Due to the high complexity, heavy utilization of resources, and evolving procurement systems in the construction industry (Olanrewaju et al. 2022), construction projects are highly exposed to uncertainty and more likely negative financial implications (Akinradewo et al. 2022). Therefore, this research reveals that the contractor's financial stability and on-time payments to the contractor by the client, help mitigate schedule delays and cost overruns (Adedokun and Egbelakin 2022) and improve project success. Since evaluating the sustainability of infrastructures and large construction projects needs addressing the consumption of energy, water, and other materials, waste management, community involvement, and safety measures among others (Krajangsri and Pongpeng 2017), these measures should be considered in the procurement and tendering process. Successful contractors are also required to provide resources and employ construction techniques to execute the project in order to meet those sustainability expectations and improve project success (Carvalho and Rabechini 2017; Krajangsri and Pongpeng 2017). One of the reasons that sustainability has lower RMSE in comparison with other critical success factors is the complex challenges to implementing this concept in the construction industry. On the other hand, many executives in this industry embrace sustainability in the design phase whereas they encounter several competing goals over the execution phase such as reducing energy costs and air pollution while they are inevitably utilising energy-intensive heavy equipment for their activities (Lynch 2021). Construction companies can improve sustainability of their projects by enhancing the visibility of their supply chain (Wuni and Shen 2023). This enables them to closely monitor practices of the contractors, subcontractors, logistics providers, and suppliers for sustainability. Therefore, thinking of and implementing sustainability measures are important in forecasting project success in construction industry at the onset.

Limitations and future research directions

This study provides great insights to construction project managers and construction companies to focus on more important critical success factors to achieve a higher level of project success. However, this research faces a few limitations as described below:

First, this research collected and analyzed data from medium and large construction projects of various types including residential and commercial constructions, specialized industrial constructions like those in mining or oil and gas, and infrastructure construction projects. While the developed ANFIS systems are highly accurate in forecasting project success, it is recommended that future studies focus on specific types of construction projects to provide specialized insights.

Second, this research collected data from project managers in Australia and New Zealand. Provided that construction projects follow a specific process to be performed and they have comparable critical success factors and success criteria except for those related to the external environments and government regulations, the results are applicable to medium and large construction projects in other geographies, too. Given that the value added of the construction industry in some countries such as the USA, China, Japan, and the UK is higher than that in Australia and New Zealand, future studies are recommended to perform a comparative analysis by forecasting project success using the proposed ANFIS systems and report the findings to highlight the potential differences.

Third, this research is limited by the nature of the ANFIS technique, which like other neural network methods, is data-hungry. The approach can benefit from gathering large sizes of data across small, medium, large, and mega construction projects for comparative analysis.

Fourth, project success especially in the construction industry might be viewed differently. Our findings are based on the opinions of project managers. So, future studies can be devoted to replicating this approach by gathering data from project stakeholders, project sponsors, and end-users of the project outputs.

Practical implications

The construction industry is the third-largest industry in Australia which produces over $367 billion in revenue and it is projected to employ over 1,263,900 people by 2025 (Australian Industry and Skills Committee 2022b). While the high employment in this industry is a proxy of its performance and necessitates a better and high-quality social life, the overall performance of this industry in terms of productivity and contribution to GDP is reported to be modest. To improve its performance and attract more investment, major construction companies are adopting innovation, digitalization, and artificial and augmented intelligence (Mordor Intelligence 2022).

Aligned with the increasing societal pressures and concerns for the environment, many Australian construction companies are moving towards adopting greener and more sustainable practices to operate more environmentally-friendly and obtain a competitive advantage over non-sustainable ones (Workfast 2017) and become more successful. Due to their nature, e.g. large size and high complexity, the inclusion of multidisciplinary stakeholders, need for careful project scheduling and risk management, dependence on transparent tendering and procurement systems, medium and large construction projects require very close management over their critical success factors and criteria to accomplish their objectives. The interdependence among the success factors and criteria identified in this research causes even higher levels of complexity and uncertainty for these projects which makes it difficult to effectively keep control over its behaviour and forecast project success. The larger the project becomes, the more interrelated and interwoven its success factors and criteria become, and the less practical the conventional approaches to measuring project success become. Given the high profile of the construction industry in Australia and New Zealand and other nations alike, therefore, it is necessary to employ advanced effective techniques to forecast project success in the early stages in order to prevent future losses. This research contributes to the practice of project management by offering a practical decision support system to forecast project success. The proposed system is not only capable of forecasting the overall project success, but also can estimate project efficiency, project effectiveness and its constituent dimensions, separately. This system directly and indirectly prevents wastage of resources by timely signalling the areas of problems, and improves stakeholder satisfaction including by keeping them informed about the status of the project and getting their advice to improve project performance.

Conclusion

The main objective of this research was to develop a decision support system using an adaptive neuro-fuzzy inference system (ANFIS) to forecast the success of medium and large construction projects. To achieve this objective, we first scanned extant literature to identify and classify the critical success factors and critical success criteria that play a role. We identified 64 critical success factors and classified them into 9 categories, i.e. project characteristics, project team, project manager, project organization, project stakeholders, external environment, sustainability, contractors, and procurement process. We identified 27 project success criteria and clustered them into five groups, i.e. project efficiency, business success, impacts on end-users, impacts on stakeholders, and impacts on the project team, from which project efficiency deals with efficiency-related criteria and the other four groups relate to project effectiveness and their combination determine overall project success. After implementing the Delphi method to gain the consensus of experts (80% or higher agreement on High and Very High importance) on the identified project success factors and success criteria, we reduced them to 53 success factors and 19 success criteria, respectively. We used five Gaussian membership functions as Very Low ($\sigma = 10.62,\ \mu = 0$), Low ($\sigma = 10.62,\ \mu = 25$), Medium ($\sigma = 10.62,\ \mu = 50$), High ($\sigma = 10.62,\ \mu = 75$) and Very High ($\sigma = 10.62,\ \mu = 100$) to represent the appropriate level of critical success factors (input variables), whereas we defined three success levels (output variable) with linear membership functions as poor (0), medium (50) and significant (100) to construct a Sugeno-type ANFIS. Prior to forecasting project success and its components, we verified the validity of the proposed ANFIS systems using a 10-fold cross-validation process and a real case study in Western Australia. To be reliable, the forecasting accuracy measures should satisfy the requirements of a good forecasting technique ($R > 0.8,\ MAPE \leq 10\%,\ RRMSE \leq 0.1, PI \leq 0.2$). Testing the proposed ANFIS systems revealed that they accurately forecast the expected outputs, e.g. project success ($R^2 = 0.97461,\ PI = 0.01589$), project efficiency ($R^2 = 0.99058$, $PI = 0.00930$), and project effectiveness ($R^2 = 0.96529$, $PI = 0.01945$). Very strong coefficients of determination (R^2) imply that the identified critical success factors (inputs) are significantly explain the variations in critical success criteria (outputs). This further confirms the comprehensiveness of the compiled sets of project success factors and success criteria. In other words, results show a very high fitness of the proposed ANFIS to real-world projects which ensure its capability to accurately forecast project success. We also compared the performance of the proposed ANFIS system with some prevalent machine learning techniques, i.e. support vector machine, logistic regression, decision tree, and random forest. As Table 8 reveals, the proposed ANFIS performs better than those methods in all indexes with a higher coefficient of determination (R^2) and lower MAPE, MAE, RMSE, RRMSE < and PI. This study is significant as it provides a major practical contribution to evaluating the potential of a project's success. The proposed ANFIS systems, therefore, provide practitioners, project managers, contractors, and senior executives with a reliable decision support system to foresee the overall performance of their construction projects at any stage of their life-cycle and devise appropriate corrective actions to enhance their success.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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