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Developing an Adaptive Neuro-Fuzzy Inference System for Performance Evaluation of Pavement Construction Projects

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Abstract: This study employs an adaptive neuro-fuzzy inference system (ANFIS) to identify critical success factors (CSFs) crucial for the success of pavement construction projects. Challenges such as construction cost delays, budget overruns, disputes, claims, and productivity losses underscore the need for effective project management in pavement projects. In contemporary construction management, additional performance criteria play a vital role in influencing the performance and success of pavement projects during construction operations. This research contributes to the existing body of knowledge by comprehensively identifying a multidimensional set of critical success performance factors that impact pavement and utility project management. A rigorous literature review and consultations with pavement experts identified sixty CSFs, categorized into seven groups. The relative importance of each element and group is determined through the input of 287 pavement construction specialists who participated in an online questionnaire. Subsequently, the collected data undergo thorough checks for normality, dependability, and independence before undergoing analysis using the relative importance index (RII). An ANFIS is developed to quantitatively model critical success factors and assess the implementation performance of construction operations management (COM) in the construction industry, considering aspects such as clustering input/output datasets, fuzziness degree, and optimizing five Gaussian membership functions. The study confirms the significance of three primary CSFs (financial, bureaucratic, and governmental) and communication-related variables through a qualitative structural and behavioral validation process, specifically k-fold cross-validation. The outcomes of this research hold practical implications for the management and assessment of overall performance indices in pavement construction projects. The ANFIS model, validated through robust testing methodologies, provides a valuable tool for industry professionals seeking to enhance the success and efficiency of pavement construction endeavors.

Keywords: adaptive neuro-fuzzy inference system; construction project management; pavement construction; critical success factors

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1. Introduction

In this study, we explore the significant growth and management of infrastructure and public utility projects globally, mainly focusing on logistics, transportation, and highways [1,2]. The increased collaboration among countries in specific domains and sustainability concerns has driven this rapid growth [3]. Partial ownership and shares are granted in public transportation systems and logistics routes to manage these semi-governmental enterprises.

Identifying critical success factors (CSFs) for such initiatives is crucial, and our selection is based on findings from various studies recognizing similar criteria in related domains. While operational and logistics elements influence project performance, our comprehensive analysis reveals a gap in the attention given to pavement construction within CSF analysis [4]. Although CSFs have been extensively studied in general civil projects, including pavements, less attention has been paid to the specific challenges of pavement construction.

Recognizing this gap, various authors have emphasized the importance of CSF analysis in pavement construction management [5,6]. CSFs play a vital role in understanding project success, measuring efficiency and effectiveness [4], and aligning with success-oriented approaches such as stakeholder returns [7] and sustainability [5,8,9]. However, the need arises to develop CSFs specifically tailored for pavement construction, considering the complexities and stages involved.

To address this need, we introduce the concept of pavement construction project performance (PCPP) factors. These factors are identified through a comprehensive literature review, building upon existing CSF literature and enhancing it within the context of pavement construction. The terminology shift to PCPP allows us to implement an adaptive neuro-fuzzy inference system (ANFIS) framework, considering intricate internal linkages between factors across complex tasks. Moreover, this approach facilitates input from numerous stakeholders at different project stages [10].

To gather insights for developing PCPP factors, we conducted an online questionnaire, receiving responses from 287 professionals across various sectors in both the public and private domains. This diverse input enhances the robustness and applicability of the PCPP framework. In the subsequent sections, we delve into the details of our methodology, the identified PCPP factors, and the implementation of the ANFIS model, offering a comprehensive exploration of the critical aspects of pavement construction project management.

2. Literature Review

2.1. Critical Success Factors in Pavement Construction

The CSF literature has traditionally focused on general road construction; however, it is necessary to study CSFs from the perspective of pavement construction [11]. Several authors have identified CSFs from the stakeholders' viewpoint and measured their success based on the financial returns and success of stakeholders [4]. Mok et al. [12] supplemented the theory. However, popular studies by Pinto and Slevin [7], Lima et al. [9], and Goel et al. [8] have placed a specific focus on sustainability, efficiency, time, and cost. Recently, customer satisfaction has become a key focus area [13–15]. Moreover, it places specific emphasis on external factors, including financial factors that affect a project's success. The following paragraphs provide detailed perspectives on CSFs in pavement construction and different schools of thought.

1. Stakeholder management and communication in pavement construction.

Pavement construction projects are complex endeavors that involve multiple stakeholders, intricate processes, and dynamic challenges. The effective management of these projects requires a keen focus on CSFs. Stakeholder management is a fundamental aspect of pavement construction. Engaging in and garnering support from clients, contractors, designers, subcontractors, and the workforce significantly affects project success [16]. Challenges in stakeholder management, such as insufficient engagement and unclear objectives, underscore the importance of addressing stakeholder concerns and fostering effective communication throughout the project lifecycle [17]. Mega-construction projects pose unique challenges in stakeholder management, emphasizing the need for clear objectives and collaboration for successful project completion [18]. This perspective on CSF is primarily based on effective stakeholder management and communication.

2. Sustainable practices in pavement construction.

Another growing perspective on project success associated with pavement construction involves sustainable practices. With increasing emphasis on sustainability in the global construction industry, pavement projects are no exception. Adopting circular economy principles, as advocated by Koc et al. [19], offers opportunities for sustainable pavement construction. Koc et al. [19] also stated that adopting such methods ensures better project success because sustainable practices consider the project's entire lifecycle from inception to delivery. Integrating sustainable approaches, such as recycling materials and minimizing waste, not only contributes to environmental preservation but also yields potential cost savings. However, context-specific approaches are essential when considering the unique characteristics of local environments and their constraints [19]. Embracing sustainable practices in pavement construction fosters environmental responsibility and enhances project outcomes.

3. Value management techniques for pavement construction.

Implementing value management (VM) principles in pavement construction projects is critical for their success, particularly in developing countries [20]. The effectiveness of VM is influenced by factors such as client support and the proficiency of the VM facilitator [20]. Identifying and implementing CSFs in VM leads to more efficient construction projects and optimizes value while minimizing costs and waste. The unique approach adopted through VM emphasizes understanding the direct and indirect risks that can affect a project at any stage. Because VM focuses more on the actual outputs against clearly defined key performance indicators (KPIs), this method is particularly useful to define what "success" means explicitly to a running pavement project and how far or close the project execution, project management, and contractor teams are from achieving it.

4. Organization-based factor rankings in pavement construction.

Differentiating critical success factors based on the organizational background of project participants is important in pavement construction projects [21]. Factors such as schedule adherence, budget management, and quality performance significantly influence overall project success [21]. Understanding organization-based rankings helps to tailor strategies for improved project outcomes by considering the diverse contexts in which pavement construction projects operate.

Embracing these factors will improve project outcomes, cost-effectiveness, and environmental sustainability in dynamic pavement construction landscapes. Understanding and implementing CSFs can pave the way for more resilient and successful projects. Future research should continue to evaluate CSFs in the context of emerging technologies and evolving construction practices to enhance project success in the pavement construction industry. Because the objective of this study was to further develop CSFs into actionable and quantifiable measures (PCPP), it adopted the definition of CSFs in pavement construction, as success can be directly or indirectly defined by project management, where good practices and effective ways of execution are developed and established in a non-linear way across all stages of the project lifecycle. Based on this approach, the literature was used to define PCPP using 60 factors.

2.2. Development of PCPP

Meeting stakeholder objectives is crucial when assessing the success and efficiency of a construction project. Several scholarly attempts have been made to address performance management and project success. The following sections provide a viable definition of performance management within the context of this study and explain the rationale behind selecting and utilizing PCPP across the seven classifications. The goal of performance management in construction project management is to assess and evaluate a project's efficiency and success [4]. To this end, other viewpoints and angles were presented. Mok et al. [12] inferred that stakeholders are crucial for determining the components and measurable variables that may assist in assessing the success of a construction project from the standpoint of stakeholder objectives and attainment.

Additionally, Pinto and Slevin [7] considered the time, cost, and execution of several enabling tasks. Recently, there has been a shift toward a more sustainable and integrated approach to civil projects [8,9]. As stated previously, studies on pavement project management are scarce. Circling back to the adapted definition of CSF, Cooke-Davis [22] defines PCPPs as important success factors, either direct or indirect, that are affected by project management and affect project success. They expanded the concept of crucial success elements by arguing that identifying such aspects throughout a project lifecycle is a smart practice. Based on this definition, the classifications adopted for this research were as follows: (1) operations management, (2) site operations, (3) logistical factors, (4) human-related factors, (5) bureaucracy and governance, (6) finances, and (7) communication. The detailed representations are presented in Table 1.

Table 1. Critical success factors developed for PCPP.

Classification 1: Operation Management-Related Factors	**Classification 2: Contractor/Site-Related Factors**
Establishment of a material supply management system.	Experience of the contractor.
Establishment of a quality management system.	Employment of skilled individuals to operate tools and machinery.
Establishment of a management system to mitigate surface topography problems.	Timely review of construction material prior to use (submittal review, samples).
Establishment of a change management tool to mitigate the impact of changes.	Examination of sub-contractors' qualifications.
Establishment of a health and safety management system on the construction site.	Periodic review and control of operational issues at site level between the management and operations team.
Establishment of a project management plan (PMP).	Assessment of site geological conditions.
Establishment of a site security system.	Review of existing utility maps.
Establishment of a schedule management system.	Inspecting the site before paving operation.
Employing a sub-contractor management system.	Establishment of a weather-protection system for construction materials.
Implementation of environmental management system.	Establishment of a site security system.
Setting up a conflict and claims resolution management system.	Readiness of contractor for urgent works imposed by the client.
Establishment of a risk management system.	Periodic review and management of key performance indicators (KPIs) by the contractor.
Classification 3: Logistics-Related Factors	**Classification 4: Human-Related Factors**
Establishment of a transportation system for delivery of raw materials.	Establishment of a plan for short staffing of manpower.
Establishment of a logistics management system.	Managing employee demotivation because of frequent relocations.
Establishment of a transport system for site staff.	Training programs (i.e., safety, technical, etc.) for workforce.
Enterprise resource planning software for logistic operations.	Establishment of an employee empowerment management system.
Establishment of a resources management system for interruptions during asphalt paving operations.	Measurement of employee satisfaction during project lifetime.
Availability of sufficient asphalt feeders.	Welfare of workforce.
Establishment of a maintenance management system for machinery and tools.	Monitoring the productivity of employees on a regular basis.
Classification 5: Bureaucracy- and Governance-Related Factors	Availability of incentive mechanisms for its employees by the contractor.
Staff compliance with relevant laws and regulations	Timely payment to its staff and subcontractors by the contractor.
Timely payment to the contractor by the client	Observance of the code of ethics by employees.
Effective government regulations easing import/export	**Classification 6: Financial Factors**
Timely acquisition of necessary permits by the contractor.	Availability of a system to manage finances (financial management systems).

Table 1. *Cont.*

Establishment of a control mechanism to reduce public interference.	Expenditure management and protocols on spending.
Establishment of a traffic management plan off-site.	Certification of credit payments in a timely manner.
Continually assessing stakeholder satisfaction throughout the project.	Timely communication of the contractor's payment time to the employer.
Capturing best practices and lessons learned.	Audit system to periodically assess contractors' compensation for delayed payments.
Establishment of handing over and close-out procedures.	
Classification 7: Communication-Related factors	
Establishment of a communication system (employees, stakeholders, sub-contractors, vendors, etc.).	
Communication of the project management plan (PMP) to all stakeholders.	
Conducting regular progress meetings with the employer and consultants.	
Setting up a document management system.	
Employment of information communication technology (ICT) during project administration.	
Timely communication of design issues to the client.	

2.3. ANFIS Application in Engineering, Construction, and Management Research

Aydin and Kisi [23] suggested that the complexity of construction is generally governed by complex interactions owing to the varying nature of the external environment. This presents two significant challenges when creating a model for construction: (1) multi-dimensional interactions across various data/touch points and (2) elements of probabilistic and non-probabilistic uncertainty [24]. Accurate predictions, often aided by artificial intelligence (AI), are beneficial for the construction industry [25,26].

In recent decades, there has been a notable surge in the use of neuro-fuzzy methodologies in construction and management research [26]. The neuro-fuzzy approach has recently been implemented in AI to resolve the vagueness of data and reach significant conclusions [27,28]. Naji et al. [29] asserted that fuzzy approaches offer distinct advantages over alternative decision-making provision approaches, such as the analytical order and network methods. Specifically, the authors noted that the fuzzy approach excels in establishing relationships while creating a foundation for decision-making and evaluation. Pavement performance indicators, including the IRI, ESAL, SN, and AGE data, were predicted utilizing the ANFIS method by Terzi [6]. In the work of H. Ziari et al. [30], nine variables influencing pavement condition were considered, and the accuracy of the group method of data handling (GMDH) and the adaptive neuro-fuzzy inference system (ANFIS) models in forecasting pavement performance across short and long terms of a pavement life cycle were analyzed.

Khalef and El-Adaway [31] asserted that the ANFIS technique's clustering in a fuzzy mechanism account for the uncertainty of opinions when rating an item, resulting in a more reliable model even with limited and continuous datasets. Based on recent developments in the ANFIS and its application in the construction industry to help overcome uncertainty, this study applies this technique to propose and test a PCPP model. Addressing real-world challenges often demands intelligent systems capable of exhibiting human-like expertise in a particular domain, adjusting to evolving environments, and providing explicable insights into their decision-making processes and actions. This paper aims to employ the adaptive neuro-fuzzy inference system (ANFIS). Expanding on this theme, Sadrossadat et al. [32] explored the potential use of ANFIS for predicting the resilient modulus of flexible pavement subgrade soils and obtained results that showed the method's robustness.

2.4. Point of Departure

As the construction industry strives for seamless project delivery with tight schedules, budgets, and quality constraints, understanding and harnessing the power of CSFs has become imperative. This point of departure sets the context for this study, which aims to explore and evaluate diverse perspectives surrounding CSFs in pavement construction.

Extensive research has revealed a wealth of information on CSFs, highlighting their significance in project success across various construction domains. Stakeholder management has emerged as a fundamental aspect of effective engagement and support of clients, contractors, designers, subcontractors, and the workforce. Sustainable practices like circular economy principles have garnered attention because of their environmental benefits and cost-saving potential. VM techniques and total quality management (TQM) are critical for enhancing project success, streamlining processes, and optimizing quality outcomes. Organization-based rankings further underscore the importance of tailoring strategies based on the backgrounds of the project participants.

Despite the abundance of research on CSFs in construction, there is a shortage of comprehensive studies focusing specifically on pavement construction management. This study aims to bridge this gap by consolidating and analyzing the existing literature to provide a thorough understanding of the key CSFs in pavement construction. By leveraging fuzzy inference systems (FIS) and the Delphi method, this study aims to develop a robust framework for evaluating and prioritizing CSFs in this specialized domain.

This study contributes to pavement construction management by presenting an empirical model that aids practitioners in making informed decisions, mitigating risks, and optimizing project outcomes. This study seeks to empower construction professionals to enhance their management practices and improve the overall performance of pavement construction projects by identifying and quantifying the critical factors.

3. Research Methodology

This study employed quantitative and fuzzy inference system modeling approaches to achieve its research goals. The study aimed to quantify the significance of PCPP factors identified through a comprehensive literature review. An online questionnaire was administered to a diverse group of international participants to capture perceptions that could be generalized to a larger population. The questionnaire yielded substantial data that were analyzed to derive meaningful insights.

The questionnaire used in this study consisted of three sections. The first section provided an overview of the scope of the study, the second section presented information on the practitioners' backgrounds, and the third used a five-point Likert scale to rank the significance of a particular PCPP factor. The data were analyzed to ascertain the trustworthiness of the rankings and detect intergroup disparities among the practitioners. Subsequently, the RIIs were computed for each factor. This technique, which uses ANFIS, is frequently used to detect imprecise circumstances and biased data conveyed through descriptive linguistics [29].

After completing the qualitative stage, which involved identifying pertinent factors, the ANFIS implementation process required five distinct phases to construct the proposed model. The ANFIS model was formulated by defining a fuzzy membership function linked to the input variable. Subsequently, a fuzzy clustering (FC) technique was employed to determine the most suitable number of fuzzy rules. The proposed ANFIS evaluation framework was formulated using aggregation and defuzzification techniques. The subsequent step involved developing eight ANFIS models categorized into two levels to predict the efficacy of PCPP employment. ANFIS models, specifically ANFIS 1–7, were developed to predict the PCPP primary factor groups at the initial level. Subsequently, ANFIS 8 received the inputs from the outputs of the major group elements at the second level. In the final stage, three validation techniques were used to assess the efficacy of the PCPP performance model. These methods include structural, behavioral, and k-fold cross-validation. Figure 1 depicts the process involved in the model development.

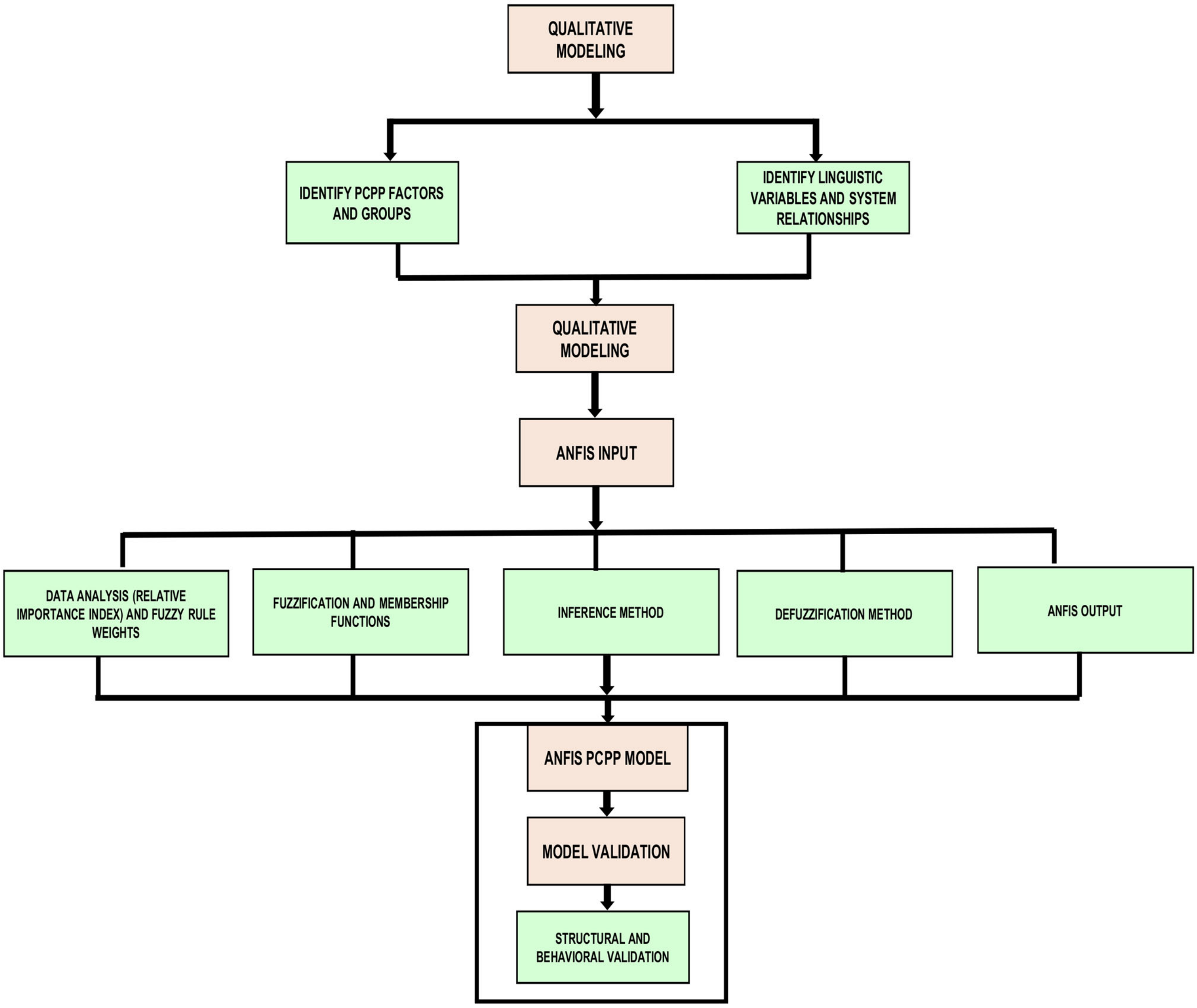


Figure 1. Process approach for evolving the ANFIS–PCPP assessment model.

3.1. Questionnaire Development and Preparing Input Linguistic Variables

The survey comprised three sections. The first section provided an overview of the study. The second section of the survey collected basic demographic data from the participants. Section three of the study pertained to the significance of the 60 PCPP metrics while delving into the importance of the seven PCPP areas. To ensure the validity of the questions, 18 construction experts and 3 university professors reviewed the questionnaire. Subsequently, a preliminary investigation was conducted involving managers employed in the construction sector, and their input was considered to enhance the questionnaire. An improved version of the survey was subsequently administered. The survey was completed by 287 participants who were asked to rate the significance of 60 PCPP factors and seven factor groups on a five-point Likert scale. The scale ranges were from 1 (not important) to 5 (extremely important), with intermediate values of 2 (slightly important), 3 (moderately important), and 4 (very important).

The feedback provided by the respondents was thoroughly examined to identify instances of carelessness or outliers. This study evaluated negligent responses using a response pattern in which a respondent may consistently choose to respond similarly to a sequence of items [33]. Outliers may indicate typical or divergent observations. This study employed group ratings and standard deviations to quantify the careless responses related to average factor rankings. SPSS version 25 software was utilized for statistical analyses, encompassing the identification of multivariate outliers through regression analyses. According to Hair et al. [33], Mahala–Nobis distances denote the distance squared and standard in units between the observation vector and sample mean vector for all variables. The probability of a Mahala–Nobis distance of less than 0.001 for 14 responses was found to be less than 0.001.

A total of 14 responses were deemed ineligible for inclusion, resulting in a final dataset of 273 responses. The study participants represented diverse managerial and technical roles, including managers, department heads, project directors, facility executives, high-ranking engineers, engineers, and quantity surveyors, spanning both public and private sectors. Most participants (75%) had over 15 years of experience in the construction sector. The study participants comprised 48% contractors, 28% consultant firms, 15% owner representatives, and 9% designers. In total, 63% of the participants were employed in the private industry, whereas 37% were engaged in public sector occupations. The study participants had diverse professional backgrounds in the construction sector, particularly infrastructure and road construction. Thus, the present study draws on insights from a diverse cohort of construction industry practitioners and specialists with substantial expertise in PCPP.

The normality of the data was assessed using the Shapiro–Wilk normality test (Ws) in SPSS. The Ws method was used to ascertain the correlation between the ideal normal scores and input data. When the score approached 1, the data exhibited a higher degree of normal distribution. Consequently, the null hypothesis was deemed acceptable for the normally distributed data. Moreover, for the data to exhibit normality, p-values indicating statistical significance must exceed a threshold of 0.05. The computed Ws values for these factors range from 0.773 to 0.863. Furthermore, according to the Ws report used as a test, the import values for the items were below 0.05. Consequently, the data exhibited a deviation from normality, as determined via the Shapiro–Wilk test (1965), thereby requiring non-parametric tests for data analysis.

A reliability analysis was conducted using SPSS to ascertain the consistency of the variables and scales, utilizing Cronbach's alpha reliability coefficient. The alpha coefficient is a statistical measure that does not rely on an assumption of data normality. It is computed by taking the mean internal correlation between each individual attribute and the number of characteristics. The coefficient alpha is a measure of internal consistency ranging from zero to one, where a higher value indicates a greater strength of consistency within the items being measured. According to Naji et al. [29], a Cronbach's alpha exceeding 0.7 indicates a highly reliable level. The alpha values of the factors in classifications 01 to 07 were 0.728, 0.821, 0.922, 0.897, 0.950, 0.879, and 0.855, respectively. Because all values exceeded a threshold of 0.7, it can be concluded that all seven classifications exhibited a high degree of reliability. The alpha coefficient for the adjusted variables was 0.899. Hair et al. [33] concluded that the individual properties of the variables were reliable for further investigation because all alpha values exceeded 0.7.

Another non-parametric test of independence that identifies the relationship between categorical variables (i.e., whether the variables are independent or related) is the chi-squared test. Naji et al. [29] employed a chi-square value to examine the presence of noteworthy distinctions in factor rankings among respondent groups. This study determined whether these differences could be attributed to gaps in knowledge, differences in decision-making abilities, bias, mixed understanding, or numerous project contexts. Naji et al. [29] employed a method to examine the distinctions between respondents from various sectors, namely groups with no representation or underrepresentation. No noteworthy differences were observed between the groups when the chi-square value surpassed the criticality value. The present study involved the computation of the critical chi-square values, which were determined to be 27.34 and 135.84. Chi-square analysis yielded outcomes indicating that all values surpassed the critical values. Based on the data characteristics, it can be concluded that the properties displayed by individual variables are dependent and suitable for additional examination.

3.2. Relative Importance Index for PCPP

The survey data were analyzed using the relative importance index (RII). This methodology has been effectively implemented in previous research endeavors [34] in the construction industry [29,35]. The RII was used to determine the hierarchy of factors and groups based on their degree of significance with respect to PCPP. The RII formula used in this study is given in Equation (1).

$$\mathrm{RII} = \sum_{j=1}^{5} \left(\mathrm{w_j}\right) / (\mathrm{h} * \mathrm{n}) \tag{1}$$

The formula for calculating the RII involves the weighting given to each factor by the respondents, denoted as $\mathrm{w_j}$, which ranges from 1 to 5. "h" represents the highest weight, which is 5, whereas "n" represents the total study participants. The RII metric was normalized within an interval of zero to one, where zero denotes non-inclusivity. A higher RII score indicates greater significance of the PCPP factor. The RIIs were subsequently ranked according to the presentation provided in Appendix A. Naji et al. [29] established that a factor is deemed significant when its RII exceeds 59%. The findings of the study revealed that each factor exhibited RII of no less than 76.66%, signifying that every factor and factor group analyzed had a noteworthy influence on the PCPP. A literature review and expert evaluation supported the validity of the procedures employed to select these factors.

4. Proposed Adaptive Neuro-Fuzzy Inference System Model

4.1. Membership Functions

When real-world variables are not easily quantified because of subjective factors, membership functions (MFs) can be used as representations, as Seresht and Fayek [36] suggested. Membership functions are used by Gao et al. [3] to transform abstract fuzzy concepts into specific values. Seresht and Fayek [37] explained that a fuzzy set can be measured using the MF. The MF was employed to delineate the correspondence between every individual point within the input space of the system and its corresponding membership value. Fundamentally, membership was quantified using numerical values ranging from zero to one. Naji et al. [29] recommended using fuzzy MFs to classify Likert scale responses. The numerical values of the MFs were determined using expert judgment or historical data, as described by Larsen et al. [38].

Gaussian MFs were employed to fuzzify and represent the inputs. This was achievable because of their ability to provide a more dependable performance evaluation system, enable a seamless transition through fuzzy levels to demonstrate the correlation between the input and output precisely, and produce fewer rules. Moreover, utilizing the Gaussian methodology yields resilient membership functions because of its ability to reduce the measure of freedom [10,29,36]. Five linguistic terms were chosen for each variable and factor to indicate the level of each input variable based on responses to a Likert scale ranging from 1 to 5. The ANFIS model defines the degree of membership within a range of zero to one. According to Jang [39], the ANFIS learning process can be divided into two distinct stages: (1) adaptation of the learning weights and (2) adaptation of the nonlinear membership functions. The distinctive attribute of ANFIS allows for the recognition of intricacy, rendering it highly appropriate for modeling intricate predicaments [29]. Figure 2 illustrates the MFs representing CF2-01, which pertains to clearly defined objectives. This factor functions as an input to produce an output for the group factor CF2, which pertains to site operations.

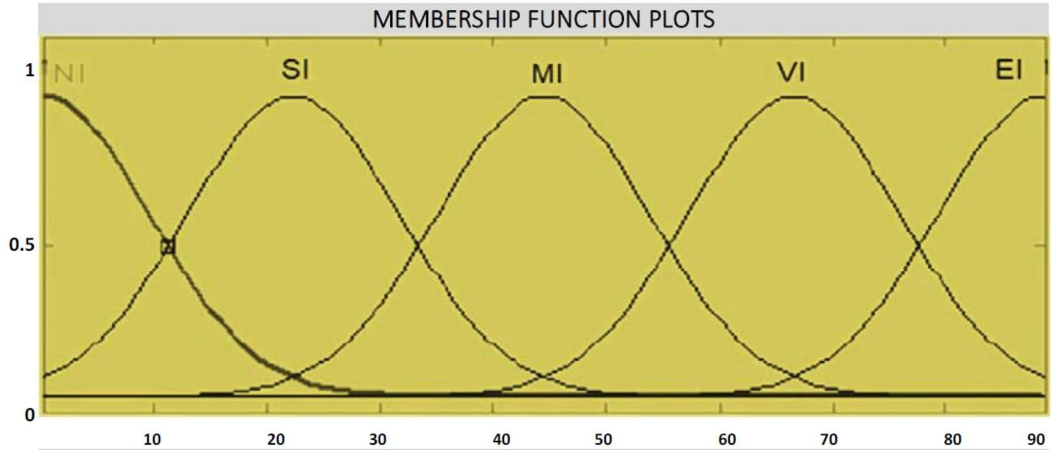


Figure 2. Membership function value—PCPP factor CF2-01.

As illustrated in Figure 2, this research made use of the five MFs: EI {σ = 10.62; μ = 100}, VI {σ = 10.62; μ = 68}, MI {σ = 10.62; μ = 45}, SI {σ = 10.62; μ = 22.5}, and NI {σ = 10.62; μ = 0.1}, where σ is the standard deviation and μ is the mean. Similar MFs were implemented using each factor as an input to obtain the factor group function as the output, which was then used as an input to get the overall PCPP index as the output.

4.2. Adaptive Neuro-Fuzzy Inference System

The ANFIS model is a hybrid system that combines the capabilities of artificial neural networks (ANNs) and inference systems. Therefore, linguistic and numeric rankings were integrated to demonstrate this issue, as shown by Naji et al. [29]. Fuzzy logic was employed to illustrate and validate the practicality of knowledge and was implemented to model the expected input and output datasets [26]. A significant limitation associated with fuzzy logic pertains to the substantial amount of time and resources required to calculate the membership functions and rules within a multifaceted system. One of the constraints of ANN is the significant effort required to determine the most suitable network configuration. Fuzzy logic and ANNs were integrated to create the ANFIS outcomes. This approach involves translating a solution into a fuzzy inference system that can be expressed using linguistic terminology. The resulting ANFIS model offers an enhanced predictive ability, leading to improved transparency and model validation [36]. The ANFIS is structured into five layers, as shown in Figure 3. The strata were arranged in the following order.

The structure includes the primary layer as the input layer, which also includes input parameters in relation to functional members and predicts the output using the Gaussian function in Equation (2).

$$\gamma_{in}(x) = e^{\frac{-(x-u_n)^2}{2\sigma_n{}^2}} \tag{2}$$

where "x" is the input value (linguistic variable), "u_n" is the center, and "σ_n" represents the spreading parameter of the Gaussian function. The c-means-based fuzzy inference system (FCM) randomly assigns a set of coefficients to different data samples and automatically chooses the number of clusters. The method continues this approach until convergence is achieved, at which time each cluster centroid "c_j" must be computed based on its membership level for "n" data points, as expressed in Equation (3).

$$c_j = \frac{\sum_{k=1}^{n} w_{i,j^m} x_i}{\sum_{k=1}^{n} w_{i,j^m}} \tag{3}$$

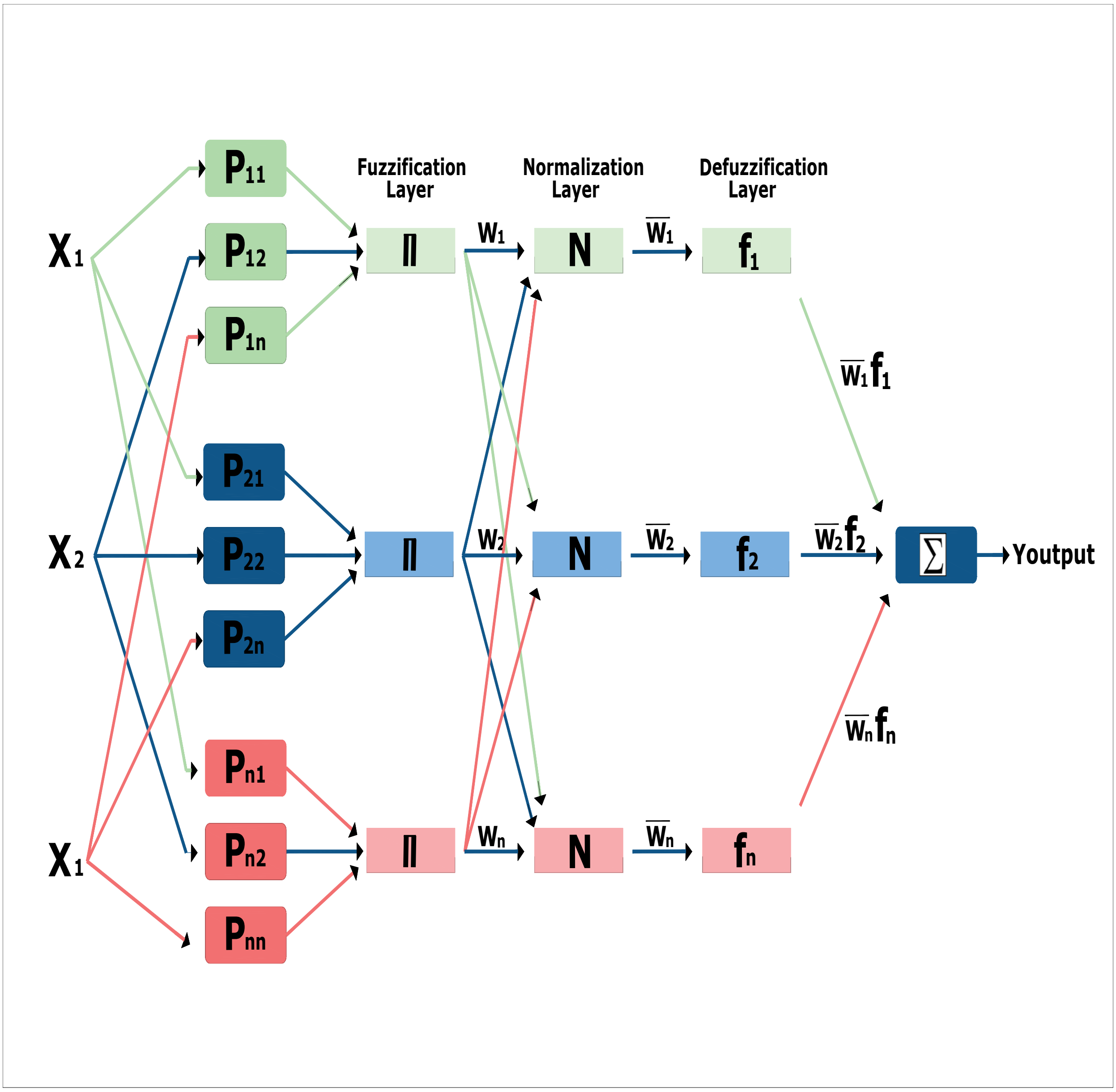


Figure 3. ANFIS as a performance evaluation index.

Based on the cluster k-th degree, any "x_i" has a set of coefficients, $w_{i,j}$ is the clustering degree, and "m" is the fuzzy partition matrix exponent. Assuming a predefined criterion, FCM separates the elements of the dataset from a finite collection. Hence, the main objective function is to be reduced to a minimum, and the "Φ" clusters can be calculated using Equation (3).

The fuzzy logic rules are based on the "If–Then" rule known as fuzzy implications or conditional statements. Hence, if dual inputs and signal outputs exist, the equation is displayed as Equation (4).

$$If\ x\ is\ T_i\ and\ y\ is\ S_i, then\ z = D \tag{4}$$

where x and y are input variables; T_i and S_i are fuzzy sets; D is the output value; and z is a crisp polynomial function of the input and output variables and is equal to $f_i(x, y)$. Based on the two variables in (5), the next layer is the fuzzification layer. The result is conveyed through the nodes expressed in Equation (5) after multiplying the input by a predetermined weight.

$$w_n = \gamma_{un}(x) \times \gamma_{vn}(y) \tag{5}$$

The member functions were normalized to calculate the weight ratio in the third layer using Equation (6).

$$\overline{w_n} = \frac{w_n}{\sum_n w_n} \tag{6}$$

In the fourth layer, the defuzzification process uses square nodes to sum the fuzzy logic rules expressed in Equation (7).

$$\overline{w_n} f_n = w_n.(t_n x + s_n y + d_n) \tag{7}$$

where t_n, s_n, and d_n are linear constraints. The last layer (fifth) aggregates the preceding layers and concludes Equation (8).

$$Output(f) = \sum_n \overline{w_n} f_n = \frac{\sum_n w_n f_n}{\sum_n w_n} \tag{8}$$

The ANFIS model comprises three distinct phases: development, training, and verification. The quantity and classification of the MFs were established during the construction phase. To construct an ANFIS model, it is necessary to partition the input and output data into sets of rules. Employing a fully connected approach has been demonstrated as a viable means of achieving this objective, as evidenced by Abdulshahed et al. [40]. Using the FC methodology involves constructing a model framework that relies on the clustering of input and output datasets, the degree of fuzziness exhibited by the clusters, and the optimization of membership functions, as noted by Tiruneh et al. [26].

The clustering process involves applying unsupervised machine learning techniques to partition a given dataset into distinct clusters or groups. Within each cluster, the data points exhibit a high degree of similarity, whereas those belonging to different clusters demonstrate dissimilarity. Clusters are formed based on the proximity of the data points within the same cluster, which indicates similarity, whereas data points in different clusters are distinct in terms of their spatial arrangement [29]. The FC method enhances conventional clustering techniques by enabling a data point to be linked to multiple clusters and allocating membership likelihoods in each cluster. Furthermore, this methodology offers the benefit of enhanced precision and requires fewer regulations, as evidenced by studies conducted by Benmouiza and Cheknane [41].

Consequently, to achieve a limited number of imprecise rules, a method for generating fuzzy rules was implemented in this study, which combined the ANFIS with fuzzy clustering (FC). FC was utilized to methodically construct the fuzzy MF and a fuzzy set of rules for the ANFIS. Following the establishment of preliminary fuzzy rules, the FC method was employed to ascertain the most advantageous cluster radius values for each input and output variable. This was performed to minimize the root-mean-square error (RMSE) associated with the forecasts generated by the fuzzy rule-oriented system.

The ANFIS model employed a training dataset comprising 80% of the available data, and the remaining 20% was reserved for validation. To initiate the training process of the ANFIS model, it is necessary to generate pairs of training data that correspond to the inputs and outputs of the model. The membership function parameters can be modified during the learning process. The optimization of the aforementioned parameters was facilitated through controlled learning using the input–output datasets presented as model training data. Takagi–Sugeno fuzzy rules denote the arithmetic associations between the inputs and outputs, which are determined using variables based on fuzzy linguistics. The primary aim of the ANFIS is to integrate the benefits and principles of fuzzy logic with a neural network learning algorithm, as stated by Naji et al. [29]. Fuzzy if-rules are commonly referred to as fuzzy-dependent statements in the field of fuzzy logic. The fuzzy logic rules are based on the "If–Then" rule, known as fuzzy implications or conditional statements.

4.3. Development of the ANFIS–PCPP Assessment Model

The present study employed the ANFIS as a predictive tool to assess the success of the PCPP implementation. The analysis was based on 60 success factors for performance and the seven key groups identified by Jang [39]. The primary objective of employing the ANFIS methodology was to evaluate the correlations among the input variables, the performance factors, and the seven cluster groups, namely CF1 to CF7. This study evaluated the associations between the aforementioned groups and the success of PCPP in ascertaining the performance index value, which is contingent on the implementation efficacy of these factors. Consequently, the following connections were established for evaluation using the ANFIS:

- Level: Operational Management Systems-Related Factors (CF1) = ANFIS of (CF1-01 to CF01-12).
- Level: Site Operations-Related Factors (CF2) = ANFIS of (CF2-01 to CF2-12).
- Level: Logistics-Related Factors (CF3) = ANFIS of (CF3-01 to CF3-07).
- Level: Human-Related Factors (CF4) = ANFIS of (CF4-01 to CF4-10).
- Level: Bureaucracy- and Governance-Related Factors (CF5) = ANFIS of (CF5-01 to CF5-08).
- Level: Financial Factors (CF6) = ANFIS of (CF6-01 to CF6-05).
- Level: Communication-Related Factors (CF7) = ANFIS of (CF7-01 to CF7-06).

The present study involved the development of eight ANFIS models on dual levels aimed at forecasting the successful implementation of the PCPP. As illustrated in Figure 4, ANFIS models 1 to 7 were initially constructed to forecast the primary determinants of the PCPP clusters. Subsequently, the results stemming from the primary factors of the group were integrated into ANFIS 8 at the secondary level. The ANFIS model generated fuzzy rules based on the number of linguistic terms for each variable. In this study, 335 fuzzy rules were developed to forecast the PCPP performance index. The integration of the ANFIS with FC was utilized to implement a technique for generating fuzzy rules characterized by fuzziness. The objective of this approach was to determine the optimal number of fuzzy rules. The FC method was systematically employed to generate fuzzy membership functions (MFs) and rules as the basis for the ANFIS, as reported by Naji et al. [29]. This study employed the ANFIS toolbox in MATLAB software (R2020) to generate a model. The inputs were defined as PCPP factors, whereas the group factors represented the outputs. The inputs for the overall PCPP index were defined as the PCPP group factors, as depicted in Figure 4. The datasets were partitioned into two distinct subsets: one for training and the other for validating the model.

4.4. The Validation Principles of the PCPP Model

The model was trained and validated using two distinct approaches, structural and behavioral, as documented in previous studies [26,42]. This proposition is subsequently validated through a case study conducted by Naji et al. [29].

4.5. Structural Validation

Structural validation involves a qualitative assessment of the dimensional consistency of a given model. This is achieved by recognizing various performance factors. The preceding section discusses the derivation of the factors affecting the performance of the PCPP as part of the structural validation test. These factors were obtained through a thorough literature review and were subsequently validated by industry and RII experts.

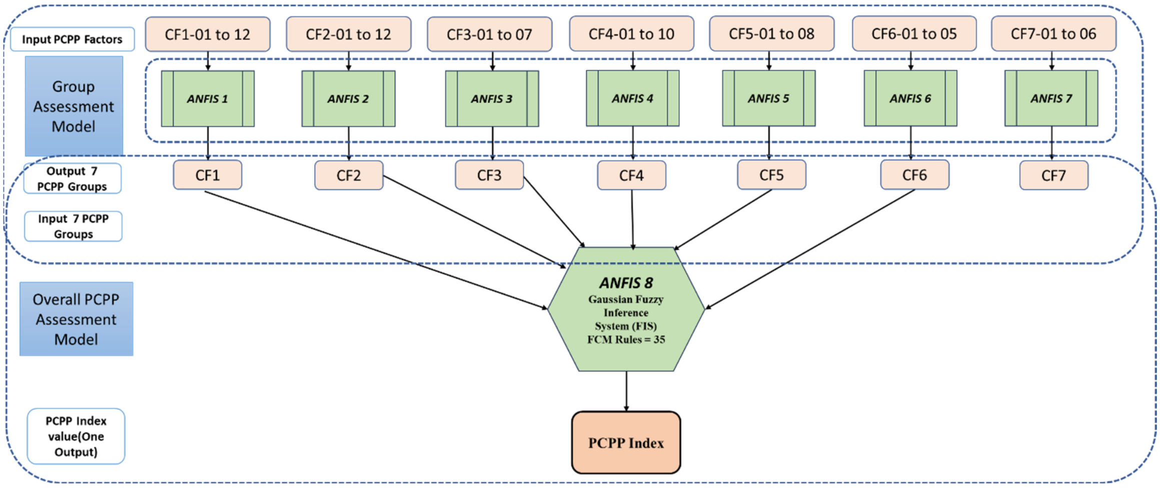


Figure 4. ANFIS–PCPP framework for assessing the overall PCPP index.

4.6. Behavioral Validation

A quantitative behavioral validity test was performed. Cross-validation with a k-fold coefficient is a commonly employed behavioral methodology for evaluating the efficacy and versatility of an ANFIS model. This technique uses statistical analysis to enable the generalization of independent datasets. Various cross-validation techniques, such as bootstrapping, the disjoint sets test, jackknife test, Monte Carlo test, and three-way split test, have been reported by Khalef and El-Adaway [31]. K-fold cross-validation was performed to mitigate the potential effects of sampling bias and overfitting. This study employs a cross-validation algorithm, specifically the k-fold method, which is a component of the jackknife test. A k-fold cross-validation approach is used to assess the effectiveness of the ANFIS model. This technique involves partitioning the complete dataset into k identical subgroups, where $k-1$ subsets are used to train the model while reserving one subset for validation or testing against other datasets [29,36]. The k-fold cross-validation technique involves repeating the entire process k times while altering the test and training data samples.

Furthermore, reducing errors using a range of error approximation metrics determined the most suitable model. The efficacy of cross-validation can be attributed to the utilization of the entire series of instances for validation and training, with each instance being exclusively employed for validation only once. The k-fold cross-validation method comprises a series of sequential steps as follows:

1. The dataset is partitioned into k homogeneous subgroups.
2. One subgroup was selected for testing, and the remaining $k-1$ subgroups were retained for training.
3. The model was calibrated using training subsets and was subsequently used to generate predictions for the test subset.
4. Various statistical tests were conducted to assess the accuracy of the optimal model prediction, including the RMSE and R^2, as outlined by Naji et al. (2022) [29].

The mean of the root-square-mean-error (RSME) was used to calculate the difference between the predicted value (by the classifier model) and the actual values of a variable. The correlation coefficient (R^2) is the correlation between the observed values of the response variable and the predicted values of the response variable made by the model [29]. Equations (9) and (10) provide mathematical formulations for the statistical error parameters and represent the mathematical expressions of the RSME and R^2, respectively.

$$\mathrm{RSME} = \frac{\Sigma(Y - X)^2}{n} \tag{9}$$

$$R^2 = \frac{(\Sigma(X,Y) - (\Sigma(X).\Sigma(Y)))^2}{\left(\Sigma\left(X^2\right) - \Sigma\left(\overline{X}\right)^2\right).\left(\Sigma\left(Y^2\right) - \Sigma\left(\overline{Y}\right)^2\right)} \quad (10)$$

where X, Y, and $\overline{X}$, are the average outcomes of the model, experiment, and model output, respectively, and n is the amount of data gathered. The model with the lowest error statistics (RMSE) and highest R^2 value was the one that was most accurately calibrated. According to previous research, the value of R^2 must be higher than 0.8 and close to 1 for a strongly linked model [29]. A study conducted by Naji et al. [29] established that utilizing 10-fold cross-validation can yield dependable variance while minimizing computational complexity. The PCPP model was developed using 287 datasets partitioned into 10 distinct subgroups. Nine models were employed for training, and the final model was reserved for testing against the optimal coefficient values obtained during the training phase. The process was iterated 10 times to ensure that validation was conducted for each generation into which the data were partitioned. The optimal coefficient was selected from a set of 10 coefficients based on its ability to produce the lowest RMSE value. Figure 5 shows a flowchart outlining the complete k-fold cross-validation process.

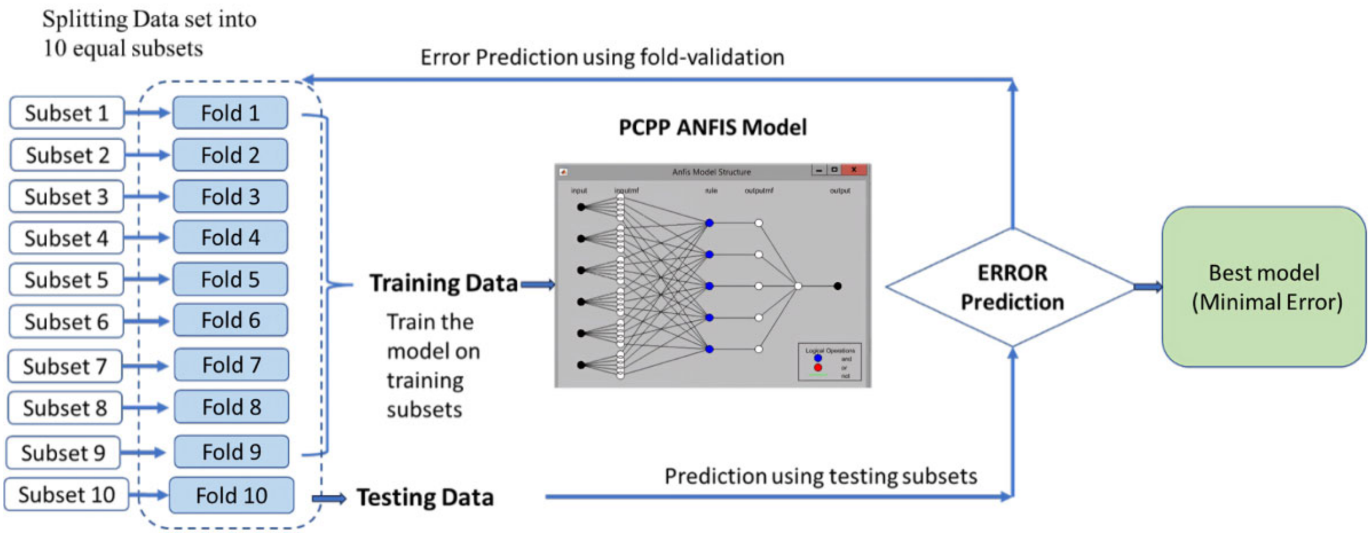
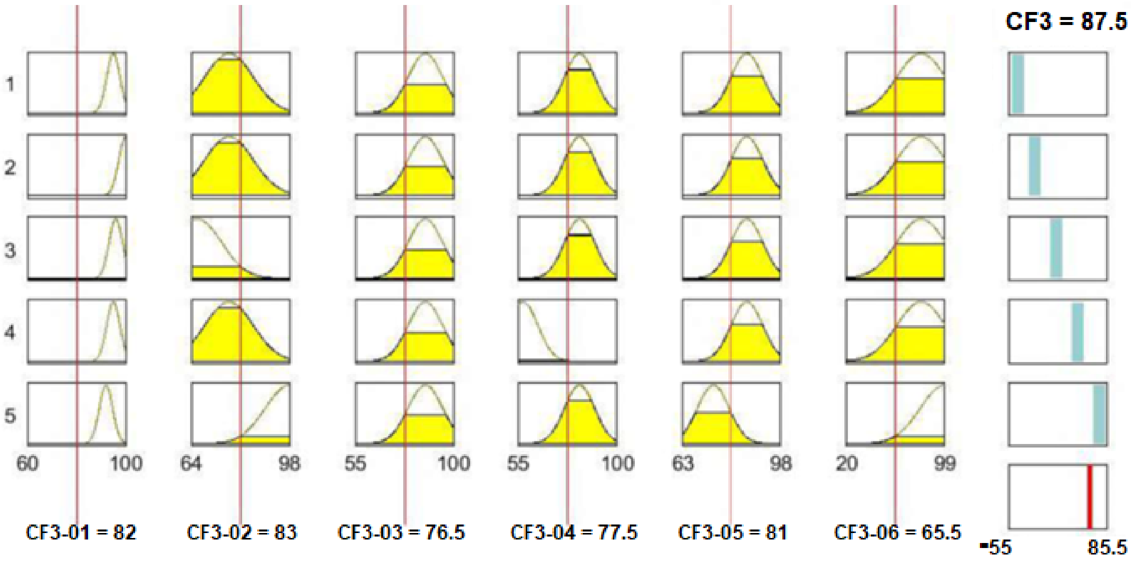


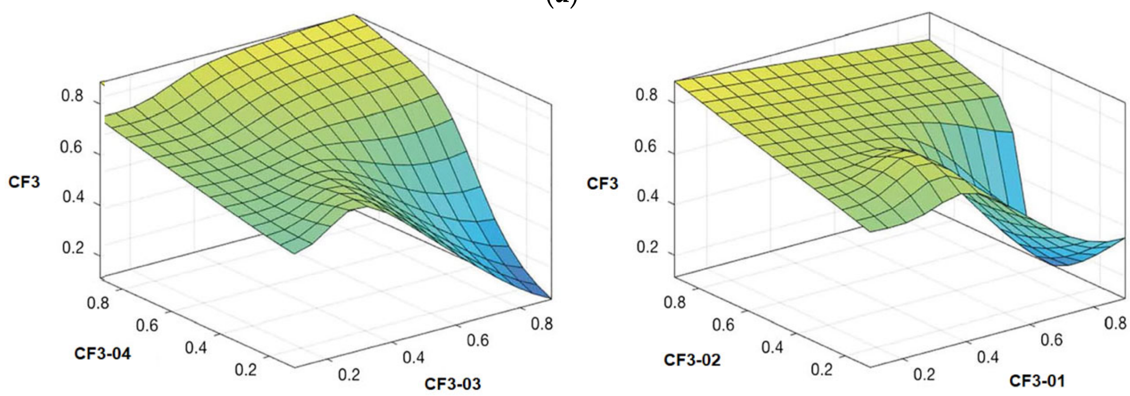
Figure 5. ANFIS–PCPP k-fold cross-validation diagram.

4.7. Results and Analysis

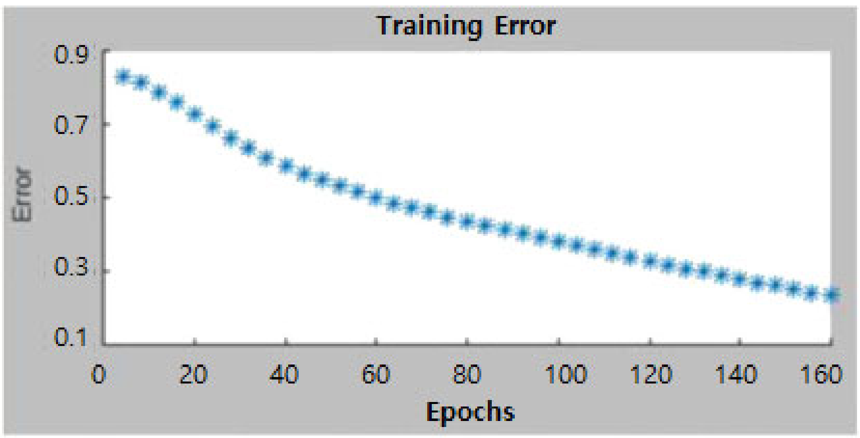
This study employed the ANFIS to construct a model for PCPP. The ANFIS methodology uses a fuzzy inference system model to convert a provided input into a desired output. This forecast entails the utilization of membership functions, fuzzy logic operators, and if–then rules within the fuzzy logic framework. This study employed FC to produce a training dataset encompassing significant synthetic data. The MATLAB ANFIS Toolbox program was used because of the considerable effort required for aggregation and defuzzification calculations. The output of the PCPP model was generated by developing eight ANFIS models using the MATLAB Toolbox. The datasets were partitioned into two segments, resulting in an outcome of 0.00975 following the training procedure, which indicated a commendable performance, as depicted in Figure 6. The network was subjected to training and testing/validation in 80% and 20% ratios, respectively. Suitable parameters for the fuzzy inference system and hybrid training methods were selected using Gaussmf. The ANFIS 3 network training utilized loaded datasets comprising six inputs and one output parameter. The ANFIS networks were trained using these datasets to ensure precise data generalization for the evaluation of the CF3. The model that underwent 157 epochs yielded the optimal training error values. Figure 5 shows a flowchart of the complete k-fold cross-validation process.



(**a**)



(**b**)



(**c**)

Figure 6. (**a**) CF3 input-output variables; (**b**) ANFIS model variables' three-dimensional surface plots; and (**c**) ANFIS training error plot.

This study involved the development of input parameters, consisting of 60 variables, output parameters comprising seven groups, and an overall PCPP indicator. Five MFs are developed for each variable. The authors employed FC and Gaussian MF to construct a comprehensive and optimal fuzzy rule set of 335 rules to characterize the behavior of the system. The outcomes of the fuzzy assessment model (ANFIS 8) were expressed through the process group indices and primary output, the overall performance index, which was quantified using the toolbox. Table 2 presents the statistical performance indicators, RMSE, and R^2.

Table 2. RMSE and R^2 values for training and validating data of ANFIS models.

ANFIS Model	RMSE	R^2
Training data (ANFIS 1)	5.556	0.958
Validating data (ANFIS 1)	3.002	0.966
Training data (ANFIS 2)	5.122	0.987
Validating data (ANFIS 2)	2.988	0.924
Training data (ANFIS 3)	6.112	0.914
Validating data (ANFIS 3)	3.123	0.928
Training data (ANFIS 4)	6.001	0.955
Validating data (ANFIS 4)	3.236	0.967
Training data (ANFIS 5)	5.891	0.988
Validating data (ANFIS 5)	2.689	0.923
Training data (ANFIS 6)	5.612	0.958
Validating data (ANFIS 6)	3.269	0.967
Training data (ANFIS 7)	5.236	0.965
Validating data (ANFIS 7)	3.211	0.954
Training data (ANFIS 8)	5.699	0.978
Validating data (ANFIS 8)	3.265	0.989

As previously stated, the dataset was divided into two subsets, with 80% allocated to the training set and 20% allocated to the testing/validation set. The process of validating data is crucial for assessing the model's efficacy and resilience. In addition, a 10-fold cross-validation was conducted for the training set. During the validation process, the training dataset was partitioned into ten subsets for each of the ten iterations. Nine of these subsets were used to train each model, and the remaining subset was used to validate and report the accuracy of each model. The accuracy of the model was reported in each iteration. Consequently, the mean accuracy of the cross-validation for each model was computed by averaging the accuracies obtained from all iterations. The average accuracy obtained through cross-validation was used to select the optimal model. Table 2 presents the statistical performance indicators RMSE and R^2 for the optimal ANFIS models numbered 1–8.

The sum squared error assessment outcomes are presented in Figure 7, where the momentum value was set to 0.9, and the learning rate varied between 0.6 and 0.9. As shown in Figure 3, a minimum RMSE of 2.689 is observed. Additionally, it is evident that the training plot (blue) closely adheres to the pattern of the data-testing plot (red). A smaller learning rate requires a larger number of epochs to attain an equivalent RMSE. However, if a significant learning rate is established, the number of required epochs is reduced. Excessively rapid convergence may lead to suboptimal global weight estimation, causing a decline in the accuracy of forecast outcomes.

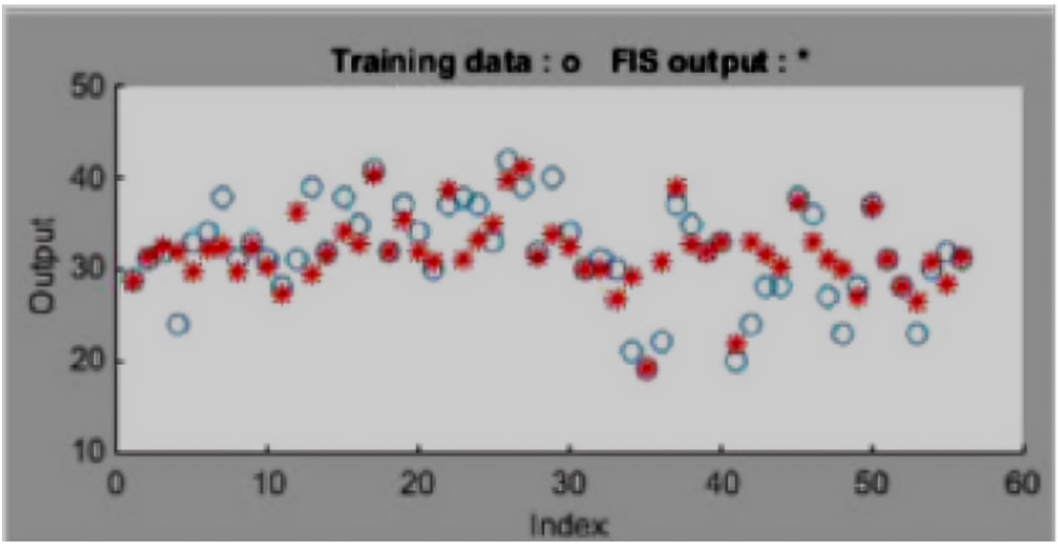


Figure 7. Training (blue) and testing (red) data plotting diagram.

4.8. Discussion of Results

The findings contribute valuable insights for effective project management in this complex and dynamic industry. The factors are discussed based on the outcomes of this research below:

Financial Factors: Sound financial management plays a pivotal role in achieving project success within pavement construction. We underscore the importance of strategic financial planning, the implementation of transparent payment policies, and the execution of stakeholder-specific financial analyses. The collaborative integration of these components plays a crucial role in ensuring the seamless execution and successful completion of pavement projects.

Bureaucratic and Governmental Factors: The role of bureaucratic processes and governance in navigating complex regulatory frameworks is highlighted. Stakeholders are urged to adeptly manage these factors, recognizing them as imperative elements contributing to project success. The nuanced understanding and effective management of bureaucratic and governmental factors are integral to overcoming regulatory challenges and ensuring project success.

Communication-Related Variables: Clear communication pathways, both within the project team and with external stakeholders, are highlighted as essential for issue resolution, risk mitigation, and the alignment of project objectives. The recognition of communication-related variables as key contributors to project success underscores the need for proactive communication strategies throughout all project phases.

In summation, this study not only advances our understanding of critical success factors but also offers practical insights for project practitioners and stakeholders in the pavement construction industry. The recommendations derived from the study, especially in the realms of financial management, regulatory navigation, and communication strategies, provide a comprehensive framework for enhancing the success rates of pavement construction projects.

Project managers can leverage the PCPP model in the ways listed below:

Informed Decision-Making:

The PCPP model serves as a predictive tool enabling project managers to make well-informed decisions. It equips them with insights at different project stages, aiding in resource allocation, risk mitigation, and project scheduling.

Risk Mitigation Strategies:

The PCPP model assists project managers in identifying and mitigating potential risks and challenges. By anticipating issues through the model's predictions, project managers can implement proactive risk mitigation strategies, reducing the likelihood of unforeseen obstacles during construction.

Optimizing Project Outcomes:

Project managers can utilize the PCPP model to optimize project outcomes. The model's ability to provide insights into critical success factors will help project managers prioritize efforts and allocate resources effectively for enhanced project performance.

5. Conclusions

This study utilized an adaptive neuro-fuzzy inference system (ANFIS) to identify the CSFs in pavement construction. We collected valuable data on the CSFs specific to pavement construction by administering an online questionnaire to industry experts. The ANFIS model was then employed to analyze the relationships among these factors and assess their impact on project success. The findings revealed the key CSFs and their relative importance in the context of pavement construction projects.

The results of this study could be beneficial in the construction industry by providing insights into the prioritization of efforts and resources for effective project management. Furthermore, the application of ANFIS demonstrates its potential as a powerful tool for analyzing complex relationships and deriving meaningful conclusions in the construction domain.

The findings of this study are specific to pavement construction and may not be directly applicable to other construction sectors. Further research and validation are recommended to ensure the generalizability and applicability of the identified CSFs. Nonetheless, the results presented in this study provide a valuable foundation for future studies and the practical implementation of pavement construction.

Overall, this study contributes to the body of knowledge by providing insights into CSFs in pavement construction and showcasing the potential of ANFIS as a decision-support tool. These findings can guide industry professionals and researchers to improve project outcomes, enhance construction practices, and contribute to the advancement of the construction industry.

6. Recommendations

This study sheds light on the CSFs that drive project success in pavement construction management. This research provides valuable insights into the key elements influencing project outcomes in this domain by synthesizing the existing literature and employing advanced analytical methods, such as fuzzy inference systems (FIS) and Delphi. Several recommendations for future studies are presented to enrich our understanding and improve pavement construction practices.

First, future research should evaluate the dynamic interplay among different CSFs in pavement construction management. Researchers can uncover the complex relationships between stakeholder management, sustainable practices, VM techniques, and effective communication by conducting longitudinal studies and analyzing project data from various regions and contexts. Understanding how these factors interact with and influence each other will allow for more targeted and effective project management strategies.

Second, integrating emerging technologies, such as artificial intelligence and data analytics, holds significant promise for the construction industry, including pavement construction management. Future studies should evaluate the application of AI-powered decision support systems to optimize CSFs and enhance project performance. Leveraging AI algorithms and predictive models can provide real-time insight and facilitate proactive decision-making, leading to better project outcomes. Additionally, research efforts should be extended to encompass the impact of external factors such as regulatory changes, economic fluctuations, and geopolitical influences on pavement construction projects. Analyzing how these macro-level variables interact with CSFs can help construction stakeholders adapt to changing environments and develop resilient project management strategies.

Finally, incorporating the perspectives of multiple stakeholders, including clients, contractors, designers, and workers, is essential for comprehensive research on pavement construction management. Future studies should emphasize participatory approaches involving all relevant parties in the research process to foster a collective understanding of CSFs and promote collaborative decision-making.

By addressing these recommendations and advancing the knowledge base of critical success factors in pavement construction management, researchers can drive continual improvements in project delivery, enhance efficiency, and contribute to the sustainable development of transportation infrastructure. As the construction industry evolves, this study serves as a steppingstone toward more informed and effective decision-making, ultimately leading to the successful completion of pavement construction projects worldwide. Project management teams should pay close attention to the top three main CSF groupings—financial, bureaucratic, and governmental—and communication-related factors, based on the findings of this study. The authors advise project management teams to build additional acceptable performance indicators to monitor total project performance and establish corrective measures for underperforming areas.

This study adds to the extant body of knowledge by filling in the following knowledge gaps regarding CSF in pavement construction projects: (1) the absence of a comprehensive and accurate definition of CSFs and (2) the requirement for models to evaluate the efficacy of frameworks that predict minimizing the effects of change orders for various work conditions. The prediction model can assist owners, project management teams, decision-makers, and construction professionals in improving their CSF evaluations.

Based on the key findings of this study, project management teams should pay close attention to the top three main CSF groupings: financial, bureaucratic, government, and communication-related factors. The authors advise project management teams to build additional acceptable performance indicators to monitor total project performance and establish corrective measures for underperforming areas. The primary drawback of the proposed methodology is the possibility of subjectivity in the quantitative evaluation of the CSF elements for paving construction projects. Instructions or guidelines regarding performance indicators should be defined to ensure uniformity among assessors.

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Appendix A

Dear Respondent,

The questionnaire presented below is part of an ongoing research titled "Performance Measurement of Pavement Construction Projects Through Structural Equation Modelling" in the Department of Civil and Architectural Engineering at Qatar University.

Responding to the questions will indeed take some of your valuable time. We seek your help and guiding responses to help us identify the critical success factors that indicate performance measures for pavement construction projects. We aim to assist contractors, business owners, consultancy experts, and academics with a reliable tool to strategize in identifying action plans and project completion to abide by project milestones and achieve the desired quality. This would help avoid unnecessary costs and unwanted disputes between the various stakeholders. Responses and opinions expressed shall be kept confidential.

Thank you for your time.

7 classifications that govern 60 critical success factors are mentioned below. Kindly provide the suitable importance grade on pavement construction project success:

Importance Level–

1. Not Important
2. Slightly Important
3. Moderately Important
4. Very Important
5. Extremely Important

Example:

"Accurate estimation of essential design factors before project initiation" has a profound impact on the overall success of pavement construction projects. Thus, accurate estimation of essential design factors has an extremely important (Number 5) impact on pavement management performance.

Classification 1: Operations Management-Related Factors	Rank
Factor	
Establishment of material supply management system	
Establishment of a quality management system	
Establishment of a management system to mitigate surface topography problems	
Establishment of a change management tool to mitigate the impact of changes.	
Establishment of a health and safety management system on the construction site	
Establishment of a project management plan (PMP)	
Establishment of a site security system	
Establishment of a schedule management system	
Employing a sub-contractor management system	
Implementation of environmental management system	
Setting up a conflict and claims resolution management system	
Establishment of a risk management system	
Classification 2: Contractor/Site-Related Factors	
Factor	
Experience of the contractor	
Employment of skilled individuals to operate tools and machinery	
Timely review of construction material prior to use (submittal review, samples)	
Examination of sub-contractors' qualifications	
Periodic review and control of operational issues at site level between the management and operations team	
Assessment of site geological conditions	
Review of existing utility maps	
Inspecting the site before paving operation	
Establishment of a weather-protection system for construction materials	
Establishment of a site security system	

Readiness of contractor for urgent works imposed by the client
Periodic review and management of key performance indicators (KPIs) by the contractor
Classification 3: Logistics-Related Factors
Factor
Establishment of a transportation system for delivery of raw materials
Establishment of a logistics management system
Establishment of a transport system for site staff
Enterprise resource planning software for logistic operations
Establishment of a resources management system for interruptions during asphalt paving operations
Availability of sufficient asphalt feeders
Establishment of a maintenance management system for machinery and tools
Classification 4: Human-related Factors
Factor
Establishment of a plan for short-staffing of manpower
Managing employee demotivation because of frequent relocations
Training programs (i.e., safety, technical, etc.) for workforce
Establishment of an employee empowerment management system
Measurement of employee satisfaction during project lifetime
Welfare of workforce
Monitoring the productivity of employees on a regular basis
Availability of incentive mechanisms for its employees by the contractor
Timely payment to its staff and subcontractors by the contractor
Observance of the code of ethics by employees
Classification 5: Bureaucracy- and Governance-Related Factors
Factor
Staff compliance with relevant laws and regulations
Timely payment to the contractor by the client
Effective government regulations easing import/export
Timely acquisition of necessary permits by the contractor
Establishment of a control mechanism to reduce public interference
Establishment of a traffic management plan off-site
Continually assessing stakeholder satisfaction throughout the project
Capturing best practices and lessons learned
Establishment of handing over and close-out procedures
Classification 6: Financial Factors
Factor
Availability of a system to manage finances (financial management systems)
Expenditure management and protocols on spending
Certification of credit payments in a timely manner
Timely communication of the contractor's payment time period to the employer
Audit system periodically to assess contractors' compensation for delayed payments

Classification 7: Communication-related factors
Factor
Establishment of a communication system (employees, stakeholders, sub-contractors, vendors, etc.)
Communication of the project management plan (PMP) to all stakeholders.
Conducting regular progress meetings with the employer and consultants
Setting up a document management system
Employment of information communication technology (ICT) during project administration
Timely communication of design issues to the client

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