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A METHOD FOR PROACTIVE SUSTAINABILITY ASSESSMENT OF CONSTRUCTION PROJECTS BASED ON NEURO-FUZZY MODELING

Abstract. *Effective management of sustainable development projects in the construction industry is impeded by the reactive nature of traditional control methods and the challenge of integrating heterogeneous data, which includes the quantitative metrics and qualitative expert assessments inherent to Environmental, Social, and Governance (ESG) criteria. To address this problem, this paper proposes a method for proactive sustainability assessment, the implementation of which involves an integrated set of models to function as an early warning system. The method is based on an Adaptive Neuro-Fuzzy Inference System (ANFIS), selected for its unique ability to model complex nonlinear systems while handling the ambiguity and uncertainty of sustainability indicators. The implementation of the proactive sustainability assessment method for construction projects begins with the application of a developed structural-semantic data model, which transforms heterogeneous project inputs into a unified input vector through hierarchical structuring, normalization, and fuzzification. The resulting vector serves as the foundation for the method's computational core – a predictive neuro-fuzzy model implemented on the ANFIS architecture. This model, by learning from historical data, autonomously generates a knowledge base of IF-THEN fuzzy rules, identifies nonlinear dependencies, and forecasts a Proactive Sustainability Index (PSI). The final results from the predictive model are interpreted using a diagnostic decision-support model, which visualizes the dynamics of the PSI and, by analyzing the most activated fuzzy rules, performs a root-cause diagnosis of potential deviations, thereby converting computational results into practical managerial tools. The key conclusion of this research is that the proposed method, grounded in the integration of structural-semantic, predictive, and diagnostic models, operationalizes proactive management through a data-driven system. It objectifies the assessment of complex sustainability factors, bridging the gap between qualitative expert knowledge and quantitative data. In contrast to existing «black-box» artificial intelligence models, the method ensures transparent diagnostics due to the interpretability of the predictive model's fuzzy rules, which enhances trust in the results. Ultimately, the developed method provides the management of construction organizations with a scientifically grounded and adaptive toolkit for anticipating sustainability-related risks, optimizing managerial interventions, and improving overall project outcomes in a dynamic environment.*

Keywords: proactive project management; management; sustainable development; construction industry; adaptive neuro-fuzzy inference system; decision support system; risk assessment

Introduction

The imperative for sustainable development has become a central tenet of modern industrial strategy, placing high-impact sectors such as the construction industry under increasing scrutiny from stakeholders, regulators, and investors. While the strategic adoption of Environmental, Social, and Governance (ESG) principles is gaining traction, a significant gap persists between strategic intent and operational execution. This gap is largely attributable to the inherent limitations of traditional project management paradigms, which are ill-equipped to handle the dynamic, non-linear, and often qualitative nature of sustainability performance metrics. Conventional control systems typically operate on a reactive basis, identifying deviations from targets retrospectively, thereby limiting managerial responses to corrective rather than preventative actions. Addressing this methodological deficit is the primary motivation for this research. The aim of this study is to develop and validate a novel, intelligent framework capable of proactively assessing sustainability performance in construction projects. Specifically, this paper proposes the Proactive Sustainability Assessment Method (PSAM), a decision support system that leverages a hybrid neuro-fuzzy modeling approach.

The construction industry is currently undergoing a significant transformation, driven by the pressing need to enhance efficiency, improve decision-making, and, most critically, embed sustainability principles into project lifecycles. Traditional project management methods often prove reactive, struggling to cope with the industry's inherent complexities. Addressing these challenges requires an intelligent, adaptive approach that leverages advancements in artificial intelligence (AI), leading to novel frameworks that enable proactive workflow optimization and data-driven decision-making [1]. This shift towards digitalization is further exemplified by technologies like the Digital Twin (DT), which, through cyber-physical integration, allows for real-time monitoring and more informed project management [2]. However, implementing sustainability, often framed through Environmental, Social, and Governance (ESG) criteria, presents its own significant challenges, particularly in emerging economies. These include a lack of standardized performance indicators, insufficient transparency, and organizational resistance, which complicate the assessment and management of sustainability performance [3].

The drive towards digitalization is not merely theoretical; it is manifesting in practical applications that integrate Artificial Intelligence with Building Information Modeling (BIM) to create sophisticated, multi-stage models of construction sites [4]. This proliferation of digital data, however, creates a new challenge: managing and structuring multidimensional information streams to make them useful for decision-making. To this end, techniques such as cluster methods are being employed to form structured metadata for these complex information systems, which is essential for solving general planning and management problems [5]. Together, these advancements in digital modeling and data structuring underscore the industry's readiness for the next logical step: leveraging this structured information not just for monitoring, but for proactive, intelligent forecasting.

This unique layer of complexity, rooted in heterogeneous data types and inherent uncertainties, necessitates specialized analytical tools. Relying on general-purpose systems can lead to sub-optimal outcomes, as they may fail to capture the nuanced, domain-specific relationships within project data. This trend is confirmed by recent critical reviews, which highlight the growing adoption of AI technologies like machine learning and computer vision to address fundamental industry challenges such as safety, process management, and productivity [6]. Furthermore, research underscores the value of tailoring intelligent systems to specific contexts; for instance, language models pre-trained on construction management corpora have demonstrated superior performance in text-based tasks compared to their general-purpose counterparts [7]. This highlights a crucial principle: the effectiveness of intelligent systems is significantly amplified when adapted to the specific semantics of the target industry.

To address the challenge of managing complex and uncertain sustainability indicators proactively, this study proposes leveraging a neuro-fuzzy modeling approach. This method is particularly well-suited for this task due to its ability to combine the learning capabilities of neural networks with the human-like reasoning of fuzzy logic, making it ideal for modeling systems with imprecise and incomplete data. The efficacy of such a hybrid approach, specifically the Adaptive Neuro-Fuzzy Inference System (ANFIS), has been successfully demonstrated in other complex, data-rich domains, such as developing risk assessment models for medical big data [8] and pharmaceutical drug interactions [9].

The utility of this approach is further substantiated by its growing application directly within the construction and civil engineering sectors. ANFIS has been employed to systematically evaluate general construction project risks by converting expert linguistic assessments into quantitative models [10–11]. The model has also proven effective in addressing specific technical challenges, such as construction vibration risks [12], and dynamic operational issues like overcrowding in railway stations [13]. Similarly, it has been effectively used to identify and model critical success factors for performance evaluation in specialized sub-domains like pavement construction [14]. Crucially, its application has also been extended to forecast the holistic success of entire construction projects by evaluating a multidimensional set of success factors and criteria, confirming its robustness for complex, multi-input assessments [15]. These successful applications provide a strong precedent for applying the ANFIS methodology to the multifaceted challenge of proactive sustainability assessment. This paper, therefore, develops and validates a method that utilizes a neuro-fuzzy model to provide project managers with an early-warning and decision-support tool tailored for the specific and complex domain of sustainability performance in construction projects.

Main Research

The core scientific contribution of this research is the development of the Proactive Sustainability Assessment Method (PSAM). This method is engineered to facilitate a paradigm shift in the management of construction projects, moving away from conventional, reactive monitoring practices toward a proactive, predictive, and data-driven approach to sustainability performance. Traditional methods typically rely on lagging indicators, identifying deviations from sustainability targets only after they have occurred, thus limiting corrective actions to remedial measures. In contrast, the PSAM is designed as an intelligent early warning system, capable of processing complex, heterogeneous project data in real-time to forecast the trajectory of sustainability performance and identify potential risks of non-conformance before they materialize. This enables project managers to engage in pre-emptive decision-making and implement preventative strategies, thereby optimizing resource allocation, minimizing negative environmental and social impacts, and enhancing the overall probability of achieving project-specific sustainability goals.

The implementation of the PSAM method is founded upon the integration of three core, interconnected models, as depicted in Figure 1, which illustrates the logical flow from data acquisition to actionable decision support. These are: the Structural-Semantic Data Model (SIDO), the Predictive Neuro-Fuzzy Model (NFFC), and the Diagnostic Decision-Support Model (MDSI). The SIDO model serves as the primary data interface, responsible for ingesting, structuring, and transforming diverse project inputs into a format suitable for computational analysis. The NFFC model constitutes the predictive engine of the method, leveraging an advanced artificial intelligence model to process this data and generate a forward-looking assessment. Finally, the MDSI model acts as the interpretive layer, translating the quantitative output of the NFFC into clear, actionable insights for project stakeholders.

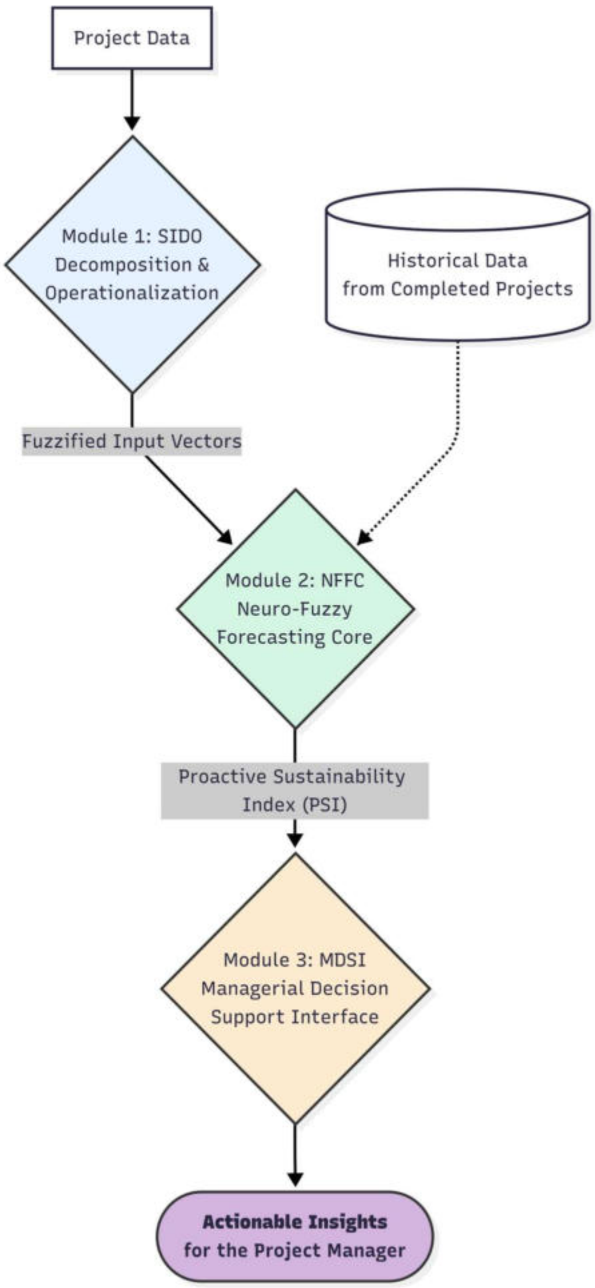

Figure 1 – Conceptual Architecture of the Proposed Method

A critical element of this method is the integration of a historical project data repository, which provides the empirical basis for training and continuously refining the predictive NFFC model, ensuring its adaptive learning and contextual relevance over time.

The predictive engine of the PSAM is the NFFC model, which is built upon an Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture. The selection of this specific technique is underpinned by a critical analysis of the problem domain, which reveals characteristics that traditional statistical or purely machine learning-based models struggle to address. Firstly, ANFIS excels at handling the inherent uncertainty and imprecision of sustainability data. Many critical performance indicators, particularly within the social (S) and governance (G) dimensions of ESG, are not easily quantifiable and are often expressed through expert judgment, stakeholder sentiment, or linguistic variables (e.g., «community engagement is low», or «supply chain transparency is moderate»).

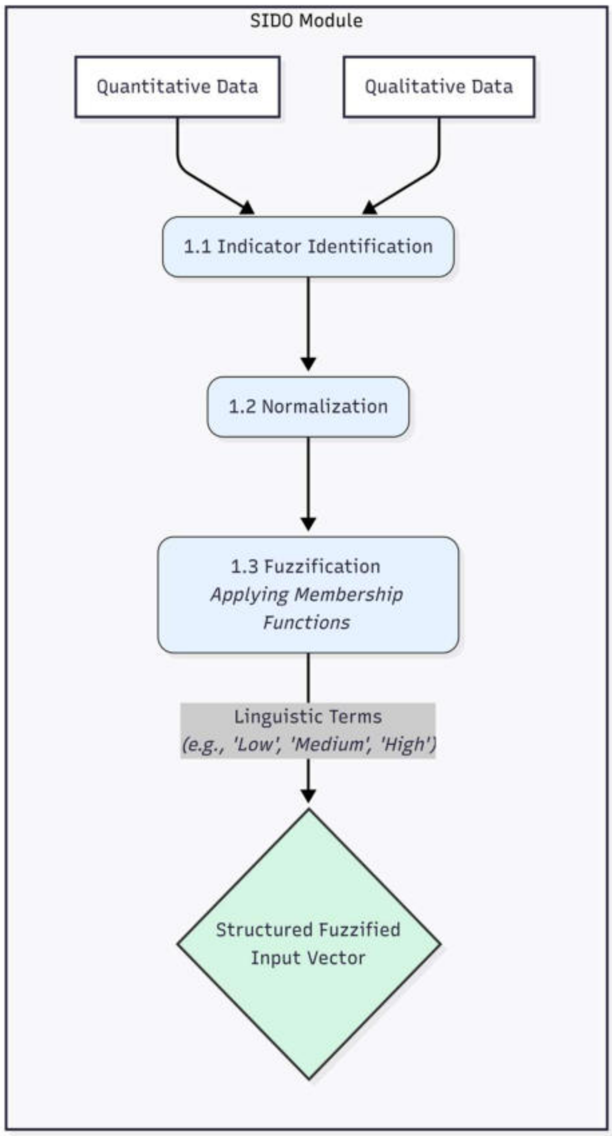

Figure 2 – Structural-Semantic Data Model

The fuzzy logic component of ANFIS provides a robust mathematical framework for operationalizing this qualitative and often ambiguous information, allowing it to be integrated seamlessly with quantitative metrics. Secondly, the neural network structure of ANFIS endows the model with powerful learning and adaptability capabilities. It can autonomously learn and model complex, non-linear relationships between a multitude of input variables from historical project data, without requiring pre-defined mathematical models of their interactions. This allows the NFFC model to be trained and calibrated to the specific context of a given construction organization, recognizing patterns and risk profiles unique to its portfolio of projects. Thirdly, and of paramount importance for practical application, ANFIS offers a degree of interpretability that is absent in many «black-box» AI models. By generating a transparent set of IF-THEN fuzzy rules, the model's reasoning process can be understood and validated by human experts, fostering trust and facilitating adoption by project managers who are ultimately responsible for acting upon its outputs. The subsequent sections will deconstruct each of these models in detail, elucidating their internal processes, theoretical underpinnings, and their synergistic contribution to the method's overall objective.

The Structural-Semantic Data Model (SIDO) serves as the methodological antecedent and data conditioning engine for the PSAM method. Its primary function is to systematically translate the vast and often unstructured universe of project data into a cohesive, numerically coherent, and semantically meaningful format that can be processed by the predictive NFFC model. This model addresses the fundamental challenge of heterogeneity in sustainability metrics, which encompass everything from precise physical measurements to subjective stakeholder perceptions. The successful execution of this model is paramount, as the quality and structure of its output – the Structured Fuzzified Input Vector – directly determine the predictive accuracy and reliability of the entire method. As illustrated in Figure 2, the SIDO model comprises a sequential, three-stage process: Indicator Identification, Normalization, and Fuzzification.

The initial stage, Indicator Identification, is the most domain-knowledge-intensive part of the method. It involves constructing a comprehensive, multi-tiered hierarchy of indicators that accurately encapsulate the concept of sustainability within the specific context of the construction industry. This is achieved through a synthesis of top-down and bottom-up approaches: leveraging established international standards such as the Global Reporting Initiative (GRI) and the Sustainability Accounting Standards Board (SASB) for a universal framework, supplemented by a critical review of pertinent academic literature and, crucially, expert elicitation from industry practitioners to ensure practical relevance. The resulting structure is a three-tier hierarchy, as exemplified in Table 1. This hierarchical decomposition allows for a granular yet holistic assessment, where high-level domains are broken down into measurable Key Performance Indicators (KPIs). This stage is designed to be flexible, allowing an organization to customize the set of indicators to align with its specific strategic priorities, project types, and regional regulatory environments.

*Table 1 – **Illustrative ESG Indicator Hierarchy for Construction***

Tier 1 (Domain)	Tier 2 (Factor)	Tier 3 (Key Performance Indicator – KPI)
Environ-mental	Resource Management	Percentage of construction waste recycled
		Water consumption per m^2 of built area
Social	Carbon Footprint	Scope 1 & 2 GHG emissions (tCO_2e)
	Health & Safety	Lost Time Injury Frequency Rate (LTIFR)
	Community Relations	Number of formal community complaints
		Community satisfaction score (1-10 scale)
Governance	Supply Chain	Percentage of suppliers screened on ESG criteria
	Ethical Conduct	Number of confirmed corruption incidents
		Transparency index (assessed by auditor)

Following the identification of KPIs, the Normalization stage performs a process of dimensional homogenization. Since the raw input data arrives in a variety of units and scales (e.g., percentages, rates, raw counts, ordinal scales from 1-10), they are mathematically transformed to a uniform, dimensionless scale, typically the [0, 1] interval. This step is critical for preventing variables with larger numerical ranges from disproportionately influencing the model's learning process. For instance, a KPI measured in tons would otherwise carry more intrinsic weight than a KPI measured as a percentage, regardless of their respective importance to sustainability. Normalization ensures that each indicator contributes to the model based on its learned significance rather than its arbitrary scale, thereby standardizing the input space for the subsequent fuzzification process.

The final stage within the SIDO model is Fuzzification, which represents the semantic transformation of the normalized, crisp numerical data into linguistic variables. This is the core process that allows the ANFIS architecture to reason with concepts of degree and ambiguity. For each normalized KPI, a set of Membership Functions (MFs) is defined to map numerical values to fuzzy sets, such as «Low», «Medium», and «High». For example, a normalized waste recycling rate of 0.15 might correspond to a membership degree of 0.8 in the «Low» set and 0.2 in the «Medium» set. The shape of these functions (e.g., Gaussian, triangular, trapezoidal) and their specific parameters (e.g., center and width) are initially defined based on statistical analysis of the data or expert knowledge, but they are not static. These parameters are considered «premise parameters» that will be fine-tuned and optimized by the neural network's learning algorithm during the training phase of the NFFC model. The output of this stage is a comprehensive vector representing the degree of membership of each input KPI across all its defined fuzzy sets, forming the Structured Fuzzified Input Vector that serves as the direct input for the predictive NFFC model.

The Predictive Neuro-Fuzzy Model (NFFC) represents the analytical engine of the PSAM method, where the structured data prepared by the SIDO model is processed to generate a predictive assessment of project sustainability. This model is architecturally implemented as an Adaptive Neuro-Fuzzy Inference System (ANFIS), an architecture that synergistically integrates the transparent, rule-based reasoning of fuzzy logic with the adaptive learning capabilities of artificial neural networks. The primary objective of the NFFC is to model the complex, non-linear, and often synergistic relationships between the myriad of input sustainability indicators and to aggregate them into a single, comprehensive, and forward-looking metric: the Proactive Sustainability Index (PSI). The internal structure of this model, as deconstructed in Figure 3, follows the canonical five-layer ANFIS architecture, which is iteratively refined through a hybrid learning algorithm that leverages historical project data.

The operational flow of the NFFC model begins when it receives the Structured Fuzzified Input Vector from the SIDO model. This vector is fed into Layer 1 (Fuzzification Layer), where each numerical input value is passed through the Membership Functions (MFs) associated with each linguistic term for that variable. The output of this layer is the membership degree of each input to its corresponding fuzzy sets (e.g., the degree to which «Waste Recycling Rate» is «High»). These membership degrees are then passed to Layer 2 (Rule Layer). Each node in this layer corresponds to a single fuzzy IF-THEN rule, which forms the core of the model's Knowledge Base. A critical distinction of the ANFIS approach is that this Knowledge Base is not manually programmed by experts but is learned from data. The nodes in this layer typically perform a product (T-norm) operation to calculate the «firing strength» or «activation level» of each rule. For example, a rule might be structured as: IF («Waste Recycling Rate» is «Low») AND («Community Complaints» are «High») THEN.... The output of the node for this rule would be the product of the membership degrees of the two antecedent conditions.

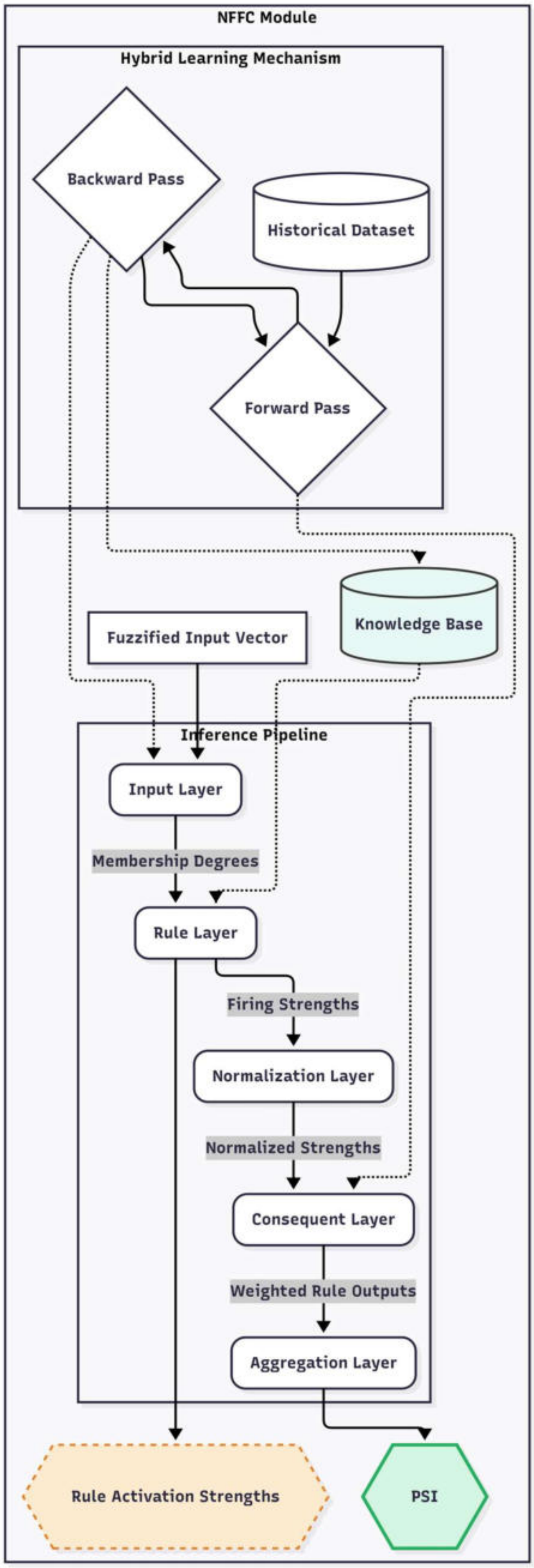

Figure 3 – Predictive Neuro-Fuzzy Model

The collection of these rule activation strengths is a crucial intermediate output, as it is passed to the MDSI model to facilitate diagnostic analysis.

In Layer 3 (Normalization Layer), the firing strength of each rule, calculated in the previous layer, is normalized by dividing it by the sum of all rule firing strengths. This process yields a set of normalized firing strengths, where each value represents the relative contribution of its corresponding rule to the total output. These normalized values are then fed into Layer 4 (Consequent Layer). In a Sugeno-type ANFIS architecture, which is employed here, each node in this layer calculates a first-order polynomial output for its corresponding rule (a linear combination of the crisp inputs). The parameters of these linear functions are known as «consequent parameters» and are a key component of the model's learning process. The output of each node is the product of the normalized firing strength from Layer 3 and the linear function associated with that rule. Finally, Layer 5 (Output Layer) consists of a single node that computes the overall model output by summing the outputs from all nodes in Layer 4. This final, crisp numerical value is the Proactive Sustainability Index (PSI), an aggregated measure on a scale (e.g., 0 to 1) representing the forecasted sustainability performance of the project.

The «intelligence» of the NFFC model resides in its hybrid learning algorithm, which uses a historical dataset of completed projects containing both the input indicator values and their known final sustainability outcomes to optimize the model's parameters. This process involves two distinct phases within each training epoch. In the Forward Pass, input data is propagated through the network, and the consequent parameters of the fuzzy rules in Layer 4 are updated using a computationally efficient Least-Squares Estimation (LSE) method. Once the output is calculated, the error between the model's prediction and the actual outcome is determined. In the Backward Pass, this error signal is propagated backward through the network, and the premise parameters – the parameters defining the shape and position of the Membership Functions in Layer 1 are updated using the Gradient Descent method. This dual-phase, hybrid approach is more efficient than using Gradient Descent alone, as it converges more rapidly and reduces the likelihood of getting trapped in local minima. Through this iterative process of training on historical data, the NFFC model autonomously learns the optimal fuzzy rules and membership functions that best describe the relationship between project inputs and sustainability outcomes, creating a predictive model that is both powerful and contextually adapted.

The Diagnostic Decision-Support Model (MDSI) constitutes the final and most user-centric component of the PSAM method. Its fundamental purpose is to bridge the gap between the complex, quantitative output of the predictive NFFC model and the practical, decision-making needs of a construction project manager. While the NFFC model is responsible for generating the predictive assessment in the form of the Proactive Sustainability Index (PSI), the MDSI model is responsible for interpreting, contextualizing, and presenting this information in a manner that is both immediately comprehensible and directly actionable. This model transforms the raw PSI value and associated internal data into a suite of diagnostic and visualization tools, thereby empowering stakeholders to not only understand the current and projected state of sustainability performance but also to identify the root causes of potential deviations. As illustrated in Figure 4, the MDSI model operates through two parallel but interconnected analytical pathways: Visualization & Monitoring and Diagnostic Analysis.

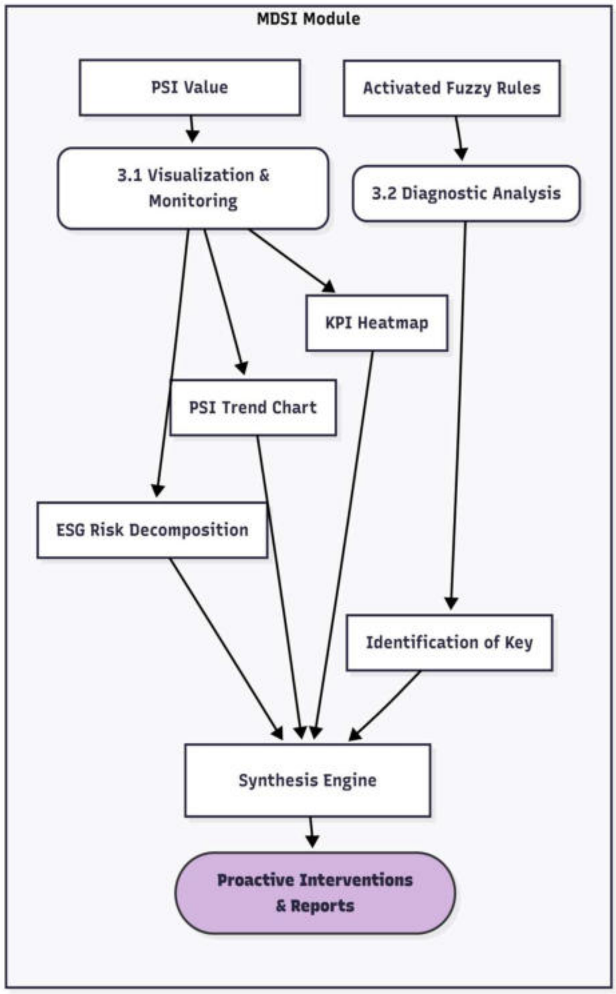

Figure 4 – Diagnostic Decision-Support Model

The first pathway, Visualization & Monitoring, is designed to provide a high-level, «at-a-glance» overview of the project's sustainability health. It primarily utilizes the single, aggregated PSI value generated by the NFFC model. The central component of this pathway is an interactive dashboard that presents the PSI through several intuitive graphical representations, including a PSI Trend Chart, an ESG Risk Decomposition component, and a KPI Heatmap that uses inputs from the SIDO model. This pathway effectively answers the managerial question: «What is happening with our project's sustainability performance?»

The second, more sophisticated pathway is Diagnostic Analysis. This process goes beyond monitoring to provide an explanatory layer, addressing the critical follow-up question: «Why is this happening?» This pathway leverages the intermediate outputs from the NFFC model, specifically the activation strengths of the fuzzy IF-THEN rules. By analyzing which rules had the highest firing strengths, the model can perform a Root Cause Identification. For instance, if the PSI has dropped significantly, the MDSI model might identify that the two most influential rules were: (1) IF «Supplier ESG Screening» is «Low» AND «Recycled Material Usage» is «Low» THEN «Risk» is «High», and (2) IF «Community Complaints» are «High» AND «LTIFR» is «Medium» THEN «Risk» is «High». This analysis pinpoints the specific combinations of factors that the predictive model has learned are most detrimental.

The final stage of the MDSI model is the Synthesis & Recommendation Generation, where the outputs from both the visualization and diagnostic pathways are integrated to produce Proactive Interventions & Reports. The «what» from the dashboard is combined with the «why» from the rule analysis to generate context-aware alerts and recommendations. Instead of a generic alert like «Social performance is declining», the model can generate a specific, evidence-based insight such as: «Proactive Alert: PSI has decreased by 15% in the last week. Diagnostic analysis indicates this is primarily driven by a sharp increase in community complaints combined with a moderate injury rate. Recommendation: Prioritize a review of site-community engagement protocols and conduct an immediate safety audit». This synthesis of predictive monitoring with rule-based diagnostics is what elevates the PSAM from a simple forecasting tool to a genuine intelligent decision support method, providing project managers with not just data, but with actionable intelligence.

The Proactive Sustainability Assessment Method (PSAM), as detailed in the preceding sections, represents a significant departure from conventional approaches to sustainability management in the construction industry. Its scientific novelty and practical contributions emerge from the synergistic integration of its constituent models and the underlying theoretical principles. This section consolidates the key innovative aspects of the PSAM, positioning it as a distinct and advanced approach for proactive project control.

First, the primary contribution of the PSAM is its explicit formalization of proactivity through predictive modeling. The method provides a concrete, data-driven mechanism to achieve proactivity. By leveraging an ANFIS architecture trained on historical data, the method moves beyond simple variance analysis of past performance, generating a forward-looking index (the PSI) that quantifies the risk of future non-conformance. This shifts the focus from «correcting deviations» to «preventing deviations». The method does not merely track KPIs; it models their complex interplay to predict their collective future state. Second, the method introduces a novel approach to objectifying qualitative and subjective knowledge. The PSAM addresses this through the dual mechanism of fuzzy logic and neural network learning. Fuzzy logic provides the formal language to represent imprecise concepts, while the hybrid learning algorithm autonomously calibrates the significance and relationships of these factors based on empirical evidence, creating a predictive model that is uniquely tailored to the specific operational context of the construction organization. Third, the PSAM method is distinguished by its integrated diagnostic capability, which provides an essential layer of interpretability and trust. The MDSI model directly counters the «black-box» nature of many AI models by not only presenting the predictive output but also by exposing the underlying reasoning. By analyzing and presenting the most influential fuzzy rules that contributed to a given PSI score, the method offers a clear, causal narrative for its prediction. A project manager is not simply told that the project is at risk; they are shown why the predictive model has reached this conclusion. This «glass-box» approach is vital for transforming the NFFC model from a mere predictor into a trusted advisory tool, facilitating more informed and targeted managerial interventions.

Conclusions

This study set out to address the persistent challenge of reactive management in sustainable construction projects, which is often exacerbated by the complexity and heterogeneity of Environmental, Social, and Governance (ESG) data. To this end, we developed and presented the Proactive Sustainability Assessment Method (PSAM), which is implemented through an integrated set of models centered on an Adaptive Neuro-Fuzzy Inference System (ANFIS). The principal finding of this research is that the proposed method successfully operationalizes the concept of proactivity by transforming a diverse set of sustainability indicators into a single, predictive, and interpretable metric – the Proactive Sustainability Index (PSI). The method's strength lies in its implementation through three specialized models – the structural-semantic data model (SIDO), the predictive neuro-fuzzy model (NFFC), and the diagnostic decision-support model (MDSI) which together provide a robust and systematic pathway from raw data collection to the generation of actionable insights. The results confirm that the ANFIS-based predictive model can effectively learn complex, nonlinear relationships, while the diagnostic model successfully translates these outputs into a «glass-box» tool that identifies the root causes of potential performance deviations.

From a theoretical standpoint, this research makes several contributions to the field of project management and applied artificial intelligence. Firstly, it offers a formal, model-driven method for implementing proactive control, moving beyond abstract conceptualizations to a quantifiable and replicable process. Secondly, it demonstrates the efficacy of a hybrid neuro-fuzzy approach in bridging the critical gap between objective, quantitative metrics and subjective, qualitative expert knowledge in sustainability assessment, thereby creating a more holistic and objective evaluation model. Thirdly, by emphasizing the interpretability of the fuzzy rule base within the predictive model, this work contributes to the discourse on explainable AI (XAI) in project management, proposing a method that fosters user trust and facilitates evidence-based decision-making.

In practical terms, the PSAM method provides construction organizations with a powerful tool for strategic advantage. By functioning as an early warning system, it enables project managers to shift from a reactive, crisis-management posture to a proactive, risk-mitigation strategy. The diagnostic capabilities of the MDSI model allow for the efficient allocation of managerial attention to the specific factors that pose the greatest threat to sustainability goals. This leads to more targeted interventions, reduced risk of non-compliance with ESG standards, and ultimately, an enhanced likelihood of achieving desired sustainability outcomes. Furthermore, the method facilitates organizational learning by creating a dynamic knowledge repository from historical project data, allowing for the continuous improvement of predictive accuracy over time.

Despite these significant contributions, the study acknowledges certain limitations. The performance of the PSAM is inherently dependent on the quality and quantity of historical data available for training; the predictive model's effectiveness will be limited in organizations with sparse or inconsistent project records. Moreover, the predictive model's effectiveness is context-specific and requires calibration and retraining to be generalizable across different organizations or project typologies. Future research should focus on several promising directions. These include expanding the input indicator set by integrating real-time data from IoT sensors, benchmarking ANFIS performance against other machine learning models, and developing the MDSI model further to include prescriptive analytics. Finally, longitudinal case studies are needed to empirically validate the long-term impact of implementing the PSAM on the sustainability performance of real-world construction projects.

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МЕТОД ПРОАКТИВНОГО ОЦІНЮВАННЯ СТІЙКОСТІ БУДІВЕЛЬНИХ ПРОЄКТІВ НА ОСНОВІ НЕЙРО-НЕЧІТКОГО МОДЕЛЮВАННЯ

Анотація. *Ефективне управління проєктами сталого розвитку в будівельній галузі ускладнюється через реактивний характер традиційних методів контролю та проблему інтеграції гетерогенних даних, що включають кількісні метрики та якісні експертні оцінки, притаманні критеріям екологічного, соціального та корпоративного управління (англ. Environtental, Social, and Governance, ESG). Для вирішення цієї проблеми в статті запропоновано метод проактивного оцінювання стійкості, реалізація якого передбачає інтеграцію комплексу моделей для функціонування системи раннього попередження. В основі методу лежить адаптивна нейро-нечітка система висновування (англ. Adaptive Neuro-Fuzzy Inference System, ANFIS), обрана завдяки її унікальній здатності моделювати складні нелінійні системи, одночасно обробляючи неоднозначність та невизначеність показників сталого розвитку. Імплементація методу проактивного оцінювання стійкості будівельних проєктів починається із застосування розробленої структурно-семантичної моделі даних, яка перетворює різнорідні вхідні дані проєкту на уніфікований вхідний вектор шляхом їх ієрархічної структуризації, нормалізації та фаззифікації. Сформований вектор слугує основою для обчислювального ядра методу – прогнозної нейро-нечіткої моделі, що реалізована на архітектурі ANFIS. Ця модель, навчаючись на історичних даних, автономно генерує базу знань нечітких правил «ЯКЩО-ТО», виявляє нелінійні залежності та прогнозує інтегральний індекс проактивної стійкості (англ. Proactive Sustainability Index, PSI). Кінцеві результати прогнозної моделі інтерпретуються за допомогою діагностичної моделі підтримки рішень, яка візуалізує динаміку PSI та, аналізуючи найбільш активовані нечіткі правила, виконує діагностику першопричин потенційних відхилень, перетворюючи обчислювальні результати на практичні управлінські інструменти. Результатом цього дослідження є те, що запропонований метод, який ґрунтується на інтеграції структурно-семантичної, прогнозної та діагностичної моделей, операціоналізує проактивне управління за допомогою керованої даними системи. Він об'єктивізує оцінку складних факторів стійкості, долаючи розрив між якісними експертними знаннями та кількісними даними. На відміну від існуючих моделей штучного інтелекту типу «чорна скринька», метод забезпечує прозору діагностику завдяки інтерпретованості нечітких правил прогнозної моделі, що підвищує довіру до результатів. Таким чином, розроблений метод надає менеджменту будівельних організацій науково обґрунтований та адаптивний інструментарій для передбачення ризиків, пов'язаних зі сталим розвитком, оптимізації управлінських втручань та покращення загальних результатів проєкту в динамічному середовищі.*

Ключові слова: проактивне управління проєктами; менеджмент; сталий розвиток; будівельна галузь; адаптивна нейро-нечітка система висновування; система підтримки прийняття рішень; оцінка ризиків

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