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Enhancing Decision Quality in Smart Manufacturing: Uncertainty-Aware Evaluation of Edge–Cloud Architectures with T-Spherical Hesitant Fuzzy Rough Sets

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ABSTRACT

In today's digitalized production environments, AI-supported systems not only transform production processes, but also complicate the nature of decisions taken in these processes. Especially in smart production scenarios where edge and cloud computing infrastructures are used together, decision processes must be managed with both low-latency local data and large-volume centralized analyses. This bidirectional data flow brings about multi-criteria decision problems that cannot be easily solved with classical algorithms due to the presence of incomplete, uncertain and unstable information. This study proposes a new decision support model for such multi-criteria and uncertain decision problems that arise in computer-aided production environments. Unlike classical data analytics methods, our model is designed based on the T-Spherical Hesitant Fuzzy Rough Set (T-SHFR) theory. While T-SHFR evaluates decision alternatives in the triangle of truth, falsehood and uncertainty, it can also systematically process incomplete or contradictory data with hesitant membership and rough set logic. In this respect, the model goes beyond the artificial intelligence applications frequently found in the literature and offers a structure where uncertainty is directly modeled. In the study, this method was integrated with edge and cloud computing architectures and the multi-criteria performance of Edge-only, Cloud-only and Hybrid approaches was evaluated; scenario-based analyses were conducted on basic parameters such as production efficiency, downtime, cost and resource usage. The findings show that the T-SHFR-based model significantly increases decision quality especially in hybrid architectures and offers higher stability and flexibility in stuations where classical methods are difficult. Thus, the proposed approach offers a holistic framework that strengthens decision making under uncertainty in computer-driven production systems.

1. INTRODUCTION

Artificial intelligence-supported production automation, sensor-based hyper-connected systems, and multi-layered data analytics have made real-time decision-making processes in today's smart manufacturing environments more complex and uncertain. The integration of edge and cloud computing technologies, which are at the center of this transformation, offers both the ability to respond to local operations with low latency and high computational power for central analytical processes. This double-layered structure directly affects not only the speed of decision-making systems, but also the quality and adaptability of decisions. However, the inherent characteristics of production data, such as incompleteness, contradiction, and uncertainty, seriously limit the effectiveness of classical decision support systems in these environments. Especially in multi-criteria decision environments, more advanced models are needed for information representation and processing due to both the imprecision of the data and the hesitant behaviors of decision makers. In order to meet this need, this study proposes a decision support framework based on the T-Spherical Hesitant Fuzzy Rough Set (T-SHFR) model. Unlike the artificial intelligence and data analytics approaches frequently used in the literature, the proposed model represents decision alternatives in a multidimensional manner with the components of truth, falsehood and uncertainty. This triple representation structure, integrated with hesitant membership theory and rough set logic, allows systematic modeling of missing or contradictory information in particular. The model has been integrated into edge and cloud computing architectures and evaluated under Edge-only, Cloud-only and Hybrid systems. The applied scenario-based analyses and sensitivity tests show that the T-SHFR model significantly increases the quality of decisions taken under uncertainty. It has been shown that it goes beyond classical methods in terms of both efficiency and flexibility, especially in hybrid architectures.

In this respect, the study presents an alternative that is highly computable, has advanced flexibility and directly models data uncertainty for multi-criteria and uncertain decision problems in computer-aided production systems. It also offers a complementary and strong alternative to artificial intelligence-based methods that are frequently used in the literature but may be limited in the face of uncertainty.

The remaining parts of this paper are structured in the following order: Section 2 summarizes the literature regarding key ideas in smart manufacturing, edge-cloud synergy, and fuzzy set theories. Section 3 gives the T-SHFR model and its formulation for use with manufacturing systems. Section 4 presents the envisioned optimization framework, while Section 5 describes methodology and findings. Section 6 concludes the paper, summarizing the findings and offering suggestions on future research work.

2. LITERATURE SURVEY

In the digital transformation of smart manufacturing systems, the integration of distributed computing technologies such as edge computing, cloud computing and data analytics plays a critical role by increasing both the response speed and computational capacity in decision-making processes. Especially in real-time production environments, the synchronous operation of the local data processing capability of edge devices and the large-scale data analytics capability of cloud systems are among the main factors determining the holistic optimization capability of the system. In this context, in recent years, numerous solution proposals have been developed in the literature for smart manufacturing systems supported by edge-cloud collaboration architectures. However, the vast majority of these solutions are inadequate in modeling uncertainties, incomplete information and instability situations arising from factors such as the density of data flow and variability in production environments. This deficiency becomes more apparent especially when it comes to Multi-Criteria Decision Making (MCDM) problems. This section focuses on three main literature areas to fill the gap above: (i) edge–cloud computing architectures and smart manufacturing integration, (ii) multi-criteria decision-making approaches and uncertainty modeling strategies, (iii) the evolution of fuzzy set theory and especially the recently proposed T-Spherical Hesitant Fuzzy Rough (T-SHFR) model. The aim is to reveal the limitations of classical methods, especially with studies in which edge and cloud computing architectures are integrated into the decision-making framework, and to methodologically substantiate why the T-SHFR model offers a more powerful and meaningful solution in this context.

The study on sustainable and digital transformation strategies to industrial systems is identified by a very wide range of interdisciplinary topics such as green mining, smart manufacturing, Industry 4.0, blockchain, and fuzzy-based decision-making. Shamsi et al. [1] present a hybrid fuzzy MCDM structure for guiding the selection of sustainable technology in mining with emphasis placed on green and climate-smart strategies. Similarly, in parallel, Khan et al. [2] suggest a knowledge-based expert system for the assessment of digital supply chain readiness, the high demand being data-driven assessment. Biswas et al. [3] present a state-of-the-art overview of green cloud computing by articulating both technological as well as environmental challenges. Akhlaqi and Hanapi [4], in their review article, center around mobile edge computing with task offloading, latency and energy efficiency constraints emphasized. Alinejad et al. [5] utilize circular intuitionistic fuzzy methods to resolve biomass management issues, focusing on smart-circular solutions. Cui et al. [6] study IoT adoptability issues in circular economy frameworks with Pythagorean fuzzy SWARA-CoCoSo, with applications in strategic manufacturing choices. Ahmmad et al. [7] employ complex q-rung orthopair fuzzy Yager operators to facilitate decision-making in environmental engineering. Govindan and Arampatzis [8] offer a combined readiness-barrier framework for Industry 4.0, while Chen et al. [9] use rough-fuzzy logic in the selection of suppliers in situations of uncertainty. Esmaeilian et al. [10] offer an introductory outline of the evolution of manufacturing, tracing its course towards intelligent systems. Talal et al. [11] propose the FWZIC-VIKOR method for evaluating the sustainability of microgrids. Bhatia and Diaz-Elsayed [12] use fuzzy TOPSIS for enabling the adoption of smart manufacturing technologies among SMEs. Mladineo et al. [13] present cooperative manufacturing alliances through network-centric approaches. Sumrit [14] uses Pythagorean fuzzy logic in IIoT readiness assessments. Singh et al. [15] and Yuan et al. [16] help by evaluating blockchain barriers and proposing dynamic rehabilitation models, respectively. The application of fuzzy logic and MCDM methods—such as AHP, DEMATEL, and TOPSIS—used across these investigations mirrors the central role of computation intelligence in advancing sustainability, resilience, and operating efficiency within digitally transforming industrial ecosystems.

The existing literature provides a comprehensive review of multi-criteria decision-making (MCDM) techniques and fuzzy-based models for evaluating technological change, sustainability, and innovation across different industrial applications. Esangbedo et al. [17] present a grey ordinal pairwise comparison MCDM model for evaluating Human Resource Information Systems with an emphasis on dealing with decision uncertainty. Jena and Patel [18] propose a fuzzy hybrid model to implement Industry 4.0 approaches in the Indian automotive industry with sustainability considerations. Ogundoyin and Kamil [19] utilize Fuzzy-AHP to prioritize trust factors in fog computing, addressing service reliability in edge environments. Molavi et al. [20] examine sustainable financial infrastructure in volatile economies using fuzzy MCDM, considering open service innovation governance. Abu-Lail et al. [21] suggest a Circular-Fermatean fuzzy model to analyze Industry 4.0 initiatives for SMEs in order to enhance decision accuracy under uncertainty. Hamidi et al. [22] suggest a blockchain readiness digital maturity model with an industry adjustment strategic roadmap. Büyüközkan et al. [23] and Irannezhad et al. [24] utilize fuzzy logic to analyze blockchain readiness to increase digital supply chain networks. Shao et al. [25] explain business intelligence in the finance of a company using IoT-based, with emphasis on data visualization. Kumar et al. [26] suggest a blockchain-IoT roadmap for green logistics. Saihi et al. [27] apply a hybrid Delphi approach to identifying success factors in digital transformation of maintenance. Yu et al. [28] present spherical fuzzy logic to assess IoT barriers in sustainable supply chains. Zamani et al. [29] suggest performance indicators for emerging Technologies. Kumar et al. [30] examine industry 4.0 application challenges to ethical SME conduct. Kumar et al. [31] investigate blockchain disruptors in the petroleum supply chain. Asadi et al. [32] apply fuzzy LMAW to deploy blockchain integration in SME supply chains. Farshidi et al. [33] discuss a case study-based decision model for choosing programming language environments. Pan and Hashemizadeh [34] discuss a circular economy-based assessment model for renewable energy. Bai and Sarkis [35] critically review formal modeling of blockchain in production and supply chains. Zayat et al. [36] discuss an extensive review of MADM applications in Industry 4.0 technologies. Lastly, Alsolami et al. [37] address interoperability in IoT applications, designing a framework for heterogeneous backhauled systems. In general, the study presents growing dependence on fuzzy, grey, and hybrid MCDM solutions to handle digital transformation, sustainability, and innovation in dynamic industrial and supply chain environments.

The existing literature reveals that fuzzy logic and MCDM methods are widely and variously used around topics such as smart manufacturing, green transformation, Industry 4.0 and blockchain applications. However, these studies are mostly limited to certain sectors (mining, logistics, SMEs, etc.) or limited decision contexts (supplier selection, technology readiness, etc.); they do not cover real-time, multi-criteria and uncertainty-driven decision environments integrated into edge and cloud computing infrastructures. In addition, the proposed models are generally limited to classical fuzzy sets or basic MCDM approaches, and advanced hybrid structures where uncertainty is represented in multi-dimensional terms are not sufficiently included. This study aims to fill this gap and present a holistic decision framework that processes both structural and cognitive uncertainties with the T-Spherical Hesitant Fuzzy Rough (T-SHFR) model.

3. METHODOLOGY

This study proposes a methodology that integrates edge-cloud computing architecture with the T-Spherical Hesitant Fuzzy Rough (T-SHFR) model in order to improve decision processes involving uncertainty in smart manufacturing systems. The method aims to provide more flexible and adaptable solutions in decision environments dominated by uncertainty, instability and multi-criteria structures by combining real-time data processing at the edge layer and large-scale analysis at the cloud layer. The methodology consists of system architecture design, data preprocessing, T-SHFR modeling and multi-objective optimization stages.

3.1 Model foundations and T-SHFR theory

In this section, the theoretical foundations of the proposed decision support structure are presented through the T-Spherical Hesitant Fuzzy Rough (T-SHFR) model. The mathematical definitions of the model's core components—spherical fuzzy sets, hesitant fuzzy sets, and rough set theory—are introduced to illustrate how T-SHFR handles uncertainty, conflict, and incomplete information in decision-making environments. Furthermore, the construction of the decision matrix within the T-SHFR space is described using membership functions and approximation operators, demonstrating the model's applicability in complex multi-criteria decision-making (MCDM) scenarios, particularly in smart manufacturing contexts.

3.1.1 Spherical fuzzy sets

A spherical fuzzy set (SFS) is a recent extension of fuzzy and intuitionistic fuzzy sets, designed to represent uncertainty more flexibly in decision-making contexts. It characterizes each element by three parameters: membership degree (μ), non-membership degree (ν), and hesitancy degree (π), satisfying a spherical constraint. Formally, an SFS A in a universe X is defined as [38]:

$$A = \{(x, \mu^{a}(x), \nu^{a}(x), \pi^{a}(x)) \mid x \in X\} \text{ and spherical constraint; } \mu^{a}(x)^2 + \nu^{a}(x)^2 + \pi^{a}(x)^2 \leq 1 \; \forall\, x \in X.$$

Here, μ(x): degree of membership, ν(x): degree of non-membership, π(x): degree of hesitancy.

3.1.2 Hesitant fuzzy sets

A hesitant fuzzy set (HFS) refers to situations where the decision maker hesitates to determine a definitive membership degree for an element. More than one possible membership degree can be defined for each element. The concept was first defined by [39].

$$A = \{(x, H_{a}(x)) \mid x \in X\} \text{ and } H_{a}(x) = \{\mu_1{}^{a}(x), \mu_2{}^{a}(x), \ldots, \mu_k{}^{a}(x)\} \subseteq [0, 1]$$

Here $H_a(x)$ represents the set of all possible membership values for element x.

3.1.3 Rough sets

Rough set theory, developed by Pawlak [40], is a mathematical method used to deal with uncertainty, incompleteness, and ambiguity in data analysis. Under an equivalence relation R defined on the universe set U, for any subset A⊆U, elements that "certainly belong to A" and "probably belong to A" are defined separately.

The Lower Approximation: $A\_L = \{x \in U : [x]_R \subseteq A\}$;

The Upper Approximation: $A\_U = \{x \in U : [x]_R \cap A \neq \emptyset\}$,

Here, $[x]_R$ denotes the access class of x according to the equivalence relation R.

3.1.4 T-Spherical Hesitant Fuzzy Rough Set (T-SHFR)

T-Spherical Hesitant Fuzzy Rough Set (T-SHFR) is an integrated structure used in decision-making environments with multi-layered uncertainty and ambiguity. This model combines the concepts of T-spherical fuzzy set [41], Hesitant fuzzy set [39], Rough set theory [40] and enables modeling different levels of uncertainty with three-dimensional membership, instability and lower-upper approximate sets.

The T-Spherical Hesitant Fuzzy Rough Set (T-SHFR) model aims to model the decision process more flexibly with rough set-based lower and upper approximate sets in the case of decision maker hesitancy, triple membership (T, F, U) structure of evaluation criteria, and lack of information. This structure is directly related to the T-spherical fuzzy rough aggregation operator approach proposed by Wang [42] and the weighted T-spherical fuzzy soft rough sets developed by Zhang et al. [43]. Both studies provided a strong theoretical basis for multi-criteria group decision making (MAGDM) problems by processing three uncertainty dimensions simultaneously. In a given universe, the T-SHFR for a set A is defined as:

$$\tilde{A} = \{\left(x, \mathcal{H}(x), \mu_{\tilde{A}}(x)\right) \mid x \in X\}$$

where, $\mathcal{H}(x)$ is hesitant membership values of an element x, and $\mu_{\tilde{A}}(x) = \left(T(x), F(x), U(x)\right)$ is the T-spherical fuzzy membership function of x. For each element, the degrees of truth, falsehood and uncertainty are given, respectively. These three values must satisfy the T-spherical condition: $T(x)^t + F(x)^t + U(x)^t \leq 1$, For a universe U and a relation R, the T-SHFR is represented as: T-SHFR$(A) = \left(\underline{A}, \bar{A}, \mu_1, \mu_2, \mu_3\right)$, where μ_1, μ_2, μ_3 represent the truth, uncertainty, and falsehood membership degrees of the hesitant fuzzy sets, and the approximations $\underline{A}$ and $\bar{A}$ are derived using rough set theory.

3.1.5 Edge-cloud collaboration with T-SHFR in manufacturing optimization

The T-SHFR model is very suitable for modeling situations in edge-cloud based systems where the decision maker cannot make a definitive decision due to lack of data, time pressure or lack of expertise. For example: Edge Layer: Real-time unstable data. Cloud Layer: Reducing uncertainty through aggregate analysis. Thus, the T-SHFR model enables the system to make adaptive decisions at both local (edge) and global (cloud) levels. In smart manufacturing systems, edge-cloud collaboration and T-SHFR analysis are applied in optimizing decision-making under uncertain conditions. The idea is that by leveraging both local (edge) and global (cloud) information, along with the high-level fuzzy rough model, the manufacturing systems can adapt to real-time production status in a continuous manner while optimizing resource allocation, scheduling, and maintenance over the long term.
The cloud layer processes big data for predictive analytics, while the edge layer provides real-time input for the execution of immediate actions. The integration of T-SHFR enhances the decision-making process through handling multidimensional uncertainty and vagueness in the data, leading to more believable and dynamic decisions.

3.1.6 Approximations of T-SHFR

Let A⊆U be a set in the universe of discourse U, and R be the equivalence relation on U. Then, the lower and upper approximations of a T-SHFR set A are given by Zhang and Shu [44]:

$$\text{Lower Approximation: } \underline{A} = \{x \in U: [x]_R \subseteq A\}$$
$$\text{Upper Approximation: } \bar{A} = \{x \in U: [x]_R \cap A \neq \emptyset\}$$

The presence of the hesitant fuzzy component modifies the approximations by including multiple possible membership degrees, enriching the decision-making process.

3.1.7 Uncertainty reduction in T-SHFR

The T-SHFR model reduces uncertainty in decision-making by providing a multi-dimensional fuzzy representation. Unlike classical fuzzy sets with a single membership value, T-SHFR incorporates multiple values reflecting various levels of uncertainty. This leads to more robust and reliable decisions under incomplete or ambiguous information.

Practical Implications of T-SHFR in Smart Manufacturing

Integrating T-SHFR into edge–cloud collaborative systems is a significant innovation for intelligent manufacturing. By processing local uncertainty at the edge and global uncertainty in the cloud, the system can optimize operations in real time while effectively handling uncertainty in scheduling, resource allocation, and maintenance. This improves overall efficiency, product quality, and cost-effectiveness.

3.1.8 Existence of optimal resource allocation using T-SHFR

Optimal resource allocation can be achieved using the T-SHFR model in multi-criteria environments involving cost, production, and uncertainty in demand and machine capabilities. By applying fuzzy decision rules and metaheuristic optimization methods (e.g., genetic algorithms, PSO), T-SHFR enables dynamic and uncertainty-aware resource distribution. Let X be the set of decisions, and let the membership function μ(x) reflect T-SHFR values. The objective is to minimize cost subject to constraints on output, resource use, and time. The result is a set of optimal solutions accounting for both efficiency and uncertainty.

3.1.9 Improved decision-making performance

The integration of T-SHFR within edge–cloud infrastructures enhance the accuracy, flexibility, and reliability of decision-making in smart manufacturing. The model's multidimensional membership structure ensures more informed decisions under uncertainty, thereby increasing operational efficiency and system robustness.

3.2 System design and edge-cloud collaboration architecture

The proposed smart manufacturing architecture is built on a hybrid edge–cloud computing model, enabling efficient data processing and real-time decision-making via task distribution between edge devices and cloud servers. Edge devices, positioned close to production units (e.g., sensors, robots), handle local tasks such as real-time filtering, anomaly detection, and initial decisions. The cloud layer manages advanced analytics including performance monitoring, resource planning, and machine learning-based forecasting. The system architecture comprises edge, cloud, and communication layers. Preprocessing tasks such as noise reduction, normalization, and missing data imputation—are distributed across these layers. Edge-level preprocessing reduces data transmission by handling smoothing and feature extraction, while the cloud performs more intensive aggregation and trend analysis. To enhance system efficiency, adaptability, and resource use, the proposed optimization framework applies the T-SHFR model to key tasks such as production scheduling, resource allocation, and cost–energy optimization. Scheduling considers uncertainties in machine performance, demand variability, and resource availability. Real-time edge data and cloud history enable dynamic resource distribution, while predictive models support energy and cost efficiency. This iterative, feedback-driven process improves responsiveness to changing production conditions. Edge computing allows instant decisions with minimal latency, reacting swiftly to failures or demand shifts. Meanwhile, the cloud ensures large-scale optimization through predictive maintenance and scheduling. Their integration balances local agility with global intelligence, creating a dynamic and adaptive manufacturing system.

The core innovation lies in combining edge–cloud collaboration with T-SHFR analysis, which effectively captures uncertainty and hesitation in decision-making. The continuous data loop between layers enables real-time adjustments and long-term planning. The result is a robust, scalable decision support model for complex smart manufacturing environments.

3.3 Mathematical modeling with T-SHFR

The proposed T-Spherical Hesitant Fuzzy Rough (T-SHFR) model is designed to simultaneously support real-time decision making at the edge layer and long-term optimization functions at the cloud layer. This structure provides the opportunity to model the uncertainties effectively and hesitant evaluations frequently encountered in modern manufacturing systems. Optimization problems encountered in smart manufacturing environments are typically multi-objective, encompassing the following objectives: maximizing system efficiency, minimizing operating costs, reducing resource waste, and minimizing downtime. These objectives are formulated as a multi-objective optimization problem under uncertainty.

Objective 1: Maximizing Production Efficiency

Production performance is typically measured by output-oriented metrics [45]. The production efficiency E_p is defined as the ratio of the actual production output to the ideal production output. Mathematically:

$$E_p = \frac{\text{Actual Output}}{\text{Ideal Output}} = \frac{\sum_{i=1}^{n} \text{Output}_i}{\sum_{i=1}^{n} \text{Ideal Output}_i}$$

where, Output_i is the actual production of unit i ; Ideal Output_i is the target or ideal output for unit i.

Objective 2: Minimizing Operational Costs

The operational cost C_{op} includes energy, labor, maintenance, and raw material costs. The total operational cost is represented as [32]:

$$C_{\text{op}} = \sum_{i=1}^{n} \left(c_{\text{energy},i} + c_{\text{labor},i} + c_{\text{maintenance},i} + c_{\text{material},i}\right)$$

where, $c_{\text{energy},i}$, $c_{\text{labor},i}$, $c_{\text{maintenance},i}$, and $c_{\text{material},i}$ are the energy, labor, maintenance, and material costs associated with unit i, respectively.

Objective 3: Minimizing Downtime

Downtime D_{down} is the amount of time when machines are not in operation. The total downtime is calculated as [46]:

$$D_{\text{down}} = \sum_{i=1}^{n} \left(t_{\text{failure},i} + t_{\text{maintenance},i}\right)$$

where, $t_{\text{failure},i}$ is the downtime due to machine failure for unit i ; $t_{\text{maintenance},i}$ is the downtime due to scheduled maintenance for unit i.

3.3.1 Constraints

The optimization problem must satisfy various constraints, including production capacity, resource availability, and operational limits. The total production output must not exceed the production capacity of the system [46]:

$$\sum_{i=1}^{n} \text{Output}_i \le \text{Max Capacity}$$

where, Output_i: Actual production of unit i, "Max Capacity" is the maximum production output that the system can handle. The amount of resources (e.g., raw materials, energy, labor) available at each point in time should be sufficient to meet production requirements. Let R_j represent the available amount of resource j, and a_{ij} be the amount of resource j required for unit i. Then, the resource constraint is:

$$\sum_{i=1}^{n} a_{ij}\, \text{Output}_i \le R_j \quad \forall j \in \{1,2,\dots,m\}$$

where, a_{ij} is the amount of resource j required for production of unit i; R_j is the total available amount of resource j. The production of each unit i is dependent on the capacity of the machines available. Let M_i represent the machine capacity for unit i. The machine capacity constraint is given by:

$$\sum_{i=1}^{n} \frac{\text{Output}_i}{M_i} \le 1$$

where, M_i is the machine's operational capacity per unit of time. The total downtime in the system must not exceed a specified threshold. Let $D_{\max}$ represent the maximum allowable downtime: $D_{\text{down}} \le D_{\max}$; where, D_{down} is the total downtime; $D_{\max}$ is the allowed maximum downtime.

3.3.2 Fuzzy and rough set integration

The decision-making process in the optimization problem is affected by both uncertainty and hesitancy. To model these aspects effectively within the manufacturing system, we employ the T-Spherical Hesitant Fuzzy Rough Set (T-SHFR) approach. This model is incorporated into the objective function for resource allocation, where the fuzzy membership degrees (positive, neutral, and negative) dynamically influence the allocation process. Accordingly, the overall optimization problem is formulated as follows [47]:

$$\min \sum_{i=1}^{n} C_{\text{op},i} \cdot \mu_1(x_i) + \lambda_1 \cdot E_p \cdot \mu_2(x_i) - \lambda_2 \cdot D_{\text{down}} \cdot \mu_3(x_i)$$

where,

$C_{\text{op},i}$ is the operational cost for unit i,

E_p is the production efficiency,

D_{down} is the downtime,

$\mu_1(x_i), \mu_2(x_i), \mu_3(x_i)$ are the membership functions corresponding to the decision x_i,

λ_1, λ_2 are weighting factors to balance the importance of efficiency and downtime.

3.3.3 Dynamic resource allocation (edge-cloud collaboration)

The allocation process is governed by both real-time data (at the edge level) and predictive information across time intervals (at the cloud level). To capture this dynamic behavior, we define a time-dependent allocation function A(t), which evolves over time t based on both global and local information sources [18] (p.7):

$$A(t) = \sum_{i=1}^{n} f_{\text{edge}}(x_i) + g_{\text{cloud}}(x_i),$$

where,

$f_{\text{edge}}(x_i)$ is the resource allocation function at the edge layer,

$g_{\text{cloud}}(x_i)$ is the resource allocation function at the cloud layer,

x_i represents the decision variables for unit i.

3.3.4 Final optimization model

Combining the objective functions, constraints, fuzzy rough set integration, and dynamic resource allocation, the final mathematical optimization model is [46]:

$$\min\{\sum_{i=1}^{n} C_{\mathrm{op},i} \cdot \mu_1(x_i) + \lambda_1 \cdot E_p \cdot \mu_2(x_i) - \lambda_2 \cdot D_{\mathrm{down}} \cdot \mu_3(x_i)\}$$

Subject to:

$$\sum_{i=1}^{n} \mathrm{Output}_i \leq \mathrm{Max\ Capacity}; \sum_{i=1}^{n} a_{ij}\ \mathrm{Output}_i \leq R_j \quad \forall j \in \{1,2,\dots,m\}$$

$$\sum_{i=1}^{n} \frac{\mathrm{Output}_i}{M_i} \leq 1;\ D_{\mathrm{down}} \leq D_{\max};\ A(t) = \sum_{i=1}^{n} f_{\mathrm{edge}}(x_i) + g_{\mathrm{cloud}}(x_i)$$

This model integrates real-time operations and long-term optimization in smart manufacturing systems by leveraging edge-cloud collaboration and T-SHFR analysis to effectively address uncertainty and hesitancy.

3.3.5 Proposed strategy model for T-Spherical Hesitant Fuzzy Rough (T-SHFR) set

The proposed strategy model utilizes T-Spherical Hesitant Fuzzy Rough (T-SHFR) set theory to support decision-making and optimization in environments characterized by uncertainty, imprecision, and vagueness. It is particularly designed to address complex multi-criteria decision-making (MCDM) problems such as resource allocation, system configuration, and performance evaluation.

Both possibilities are stated as a T-Spherical Hesitant Fuzzy Rough (T-SHFR) set that provides a systematic way of defining the truth (T), falsity (F), and indeterminacy (U) of each possibility regarding different criteria while considering hesitant membership.

For a negating A_i, its membership function $\mu_{\tilde{A}_i}$ in the discourse universe X is defined as [47]:

$$\mu_{\tilde{A}_i}(x) = \left(T_{\tilde{A}_i}(x), F_{\tilde{A}_i}(x), U_{\tilde{A}_i}(x)\right);$$

where, $T_{\tilde{A}_i}(x)$ is the truth degree of the alternative for criterion x; $F_{\tilde{A}_i}(x)$ is the falsehood degree; $U_{\tilde{A}_i}(x)$ is the uncertainty degree and the membership values satisfy the condition: $T_{\tilde{A}_i}(x)^t + F_{\tilde{A}_i}(x)^t + U_{\tilde{A}_i}(x)^t \leq 1$, for some $t > 0$

Hesitant fuzzy logic enables the representation of multiple possible membership degrees for each alternative with respect to a given criterion, thereby modeling the decision maker's uncertainty or hesitation in assigning a single precise value

3.4 Evaluation and ranking

To evaluate and rank the alternatives, the T-SHFR set model integrates multi-criteria decision-making (MCDM) methods such as Fuzzy TOPSIS, VIKOR, and MOORA within the T-SHFR framework, as illustrated in Figures 1 and 2. These methods allow for robust assessment based on different perspectives—distance from ideal solutions (Fuzzy TOPSIS), compromise-based ranking (VIKOR), and ratio analysis (MOORA).

The proposed optimization approach seeks to minimize or optimize specific objectives (e.g., cost, efficiency) in the presence of multiple conflicting criteria, vagueness, and uncertainty. The uncertainty in decision-makers' preferences is modeled using T-Spherical Hesitant Fuzzy Rough (T-SHFR) sets. To identify the optimal solutions, optimization techniques such as genetic algorithms, particle swarm optimization, or linear programming can be applied within this framework in Figure 2.

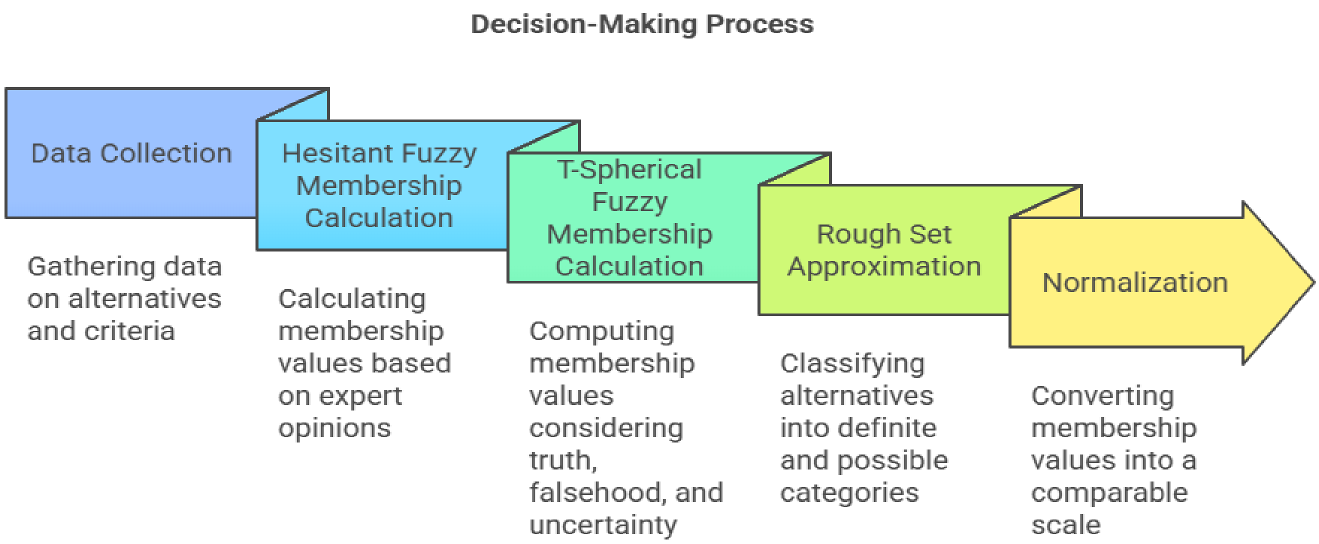

Figure 1. Decision-making process

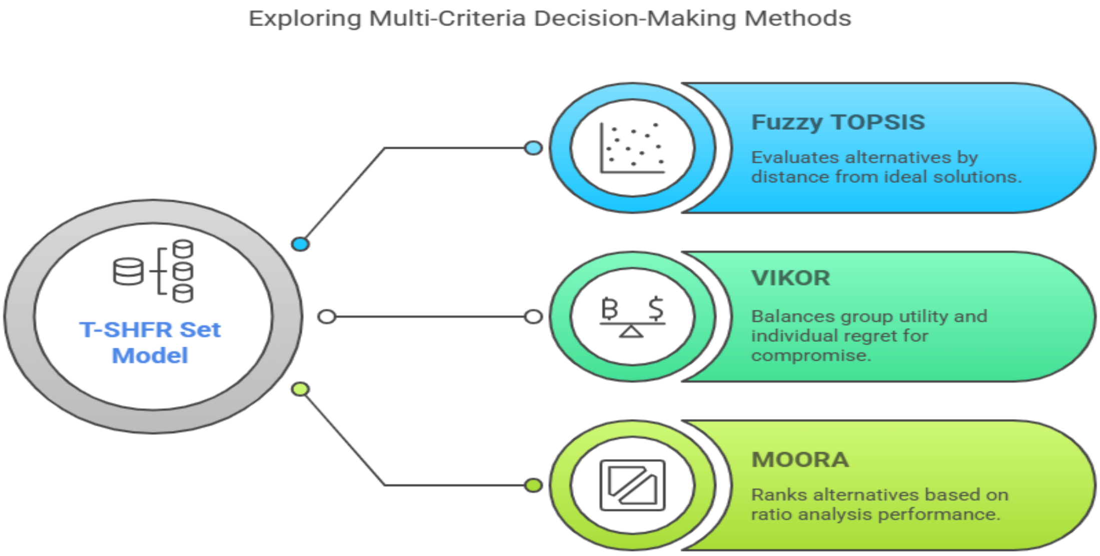

Figure 2. T-SHFR set based MCDM model

4. CASE STUDY: RESOURCE ALLOCATION IN SUPPLY CHAIN MANAGEMENT

A manufacturing company aims to select optimal suppliers based on multiple criteria such as cost, delivery time, and quality. Due to the presence of uncertainty in both the performance of suppliers and the preferences of the decision-maker, the problem is well-suited for modeling using the T-Spherical Hesitant Fuzzy Rough (T-SHFR) set framework. In this context, the performance of each supplier is evaluated using a T-SHFR set, which incorporates three membership degrees—truth (T), falsity (F), and uncertainty (U)—for each criterion. By combining the strengths of spherical fuzzy sets, hesitant fuzzy information, and rough set boundaries, the T-SHFR model provides a robust mechanism for handling vague, imprecise, and incomplete decision environments. This allows for more reliable evaluation, comparison, and ranking of supplier alternatives. Moreover, the proposed approach can be extended beyond supplier selection to encompass a broader set of applications, including resource allocation, production planning, and logistics coordination within smart manufacturing systems. When integrated with edge-cloud computing infrastructure, the model enables dynamic, data-driven decision-making that adapts to real-time operational changes. To build a comprehensive optimization framework, additional decision parameters and operational tasks can also be integrated. These are outlined below to further support intelligent supply chain and resource planning strategies.

4.1 Evaluation parameters

The evaluation of smart manufacturing strategies under edge-cloud collaboration considers multiple performance parameters:

Latency (L): Network-induced delay in processing and communication. Energy Consumption (E): Total energy usage of computing and communication components. Resource Utilization (R): Efficiency in the use of computing, storage, and network resources. Production Throughput (PT): Number of completed products or tasks per time unit. Production Cost (C): Total cost, including hardware, software, energy, and maintenance. Maintenance Time (MT): Downtime allocated to maintenance and servicing activities. Quality Control (QC): The system's ability to maintain product or service standards. Energy Efficiency (EE): Ratio of productive energy usage to total consumption. Fault Tolerance (FT): Capability to maintain function despite component failures. Data Transfer Time (DTT): Time required for inter-system data exchange. Security & Privacy (SP): Measures ensuring data confidentiality and integrity. Downtime (DT): Total non-operational time of the system. Supply Chain Coordination (SCC): Effectiveness in integrating with external supply chain elements.

Each alternative (e.g., Edge-only, Cloud-only, Hybrid) is evaluated using a T-Spherical Hesitant Fuzzy Rough (T-SHFR) set, where each criterion is represented by a triplet of truth (T), falsity (F), and uncertainty (U) values. A decision matrix, such as the one illustrated in Table 1, captures the evaluations across alternatives and criteria. This matrix enables a comprehensive assessment of system performance, allowing decision-makers to quantify trade-offs and select the optimal configuration for smart manufacturing under uncertainty. To implement the T-SHFR-based evaluation, the decision matrix compares alternatives across the selected criteria using fuzzy hesitant judgments. The T-SHFR set offers a structured representation of both subjective assessments and objective performance data, facilitating robust multi-criteria decision-making in uncertain environments.

In this study, a hybrid data collection strategy was adopted. For quantitative criteria such as production cost, energy usage, and latency, numerical estimates were used in the form of Triangular Fuzzy Numbers (TFNs) based on technical specifications, historical performance logs, or simulation results. In contrast, qualitative and subjective criteria such as scalability, uncertainty handling, and flexibility were assessed through expert judgment. Three experts independently rated each alternative, and the final values were obtained by averaging their scores. This dual approach ensured both empirical grounding and expert insight in the evaluation process. The normalized values for each of the alternatives (Edge-only, Cloud-only, Hybrid) for each criterion are determined. These values indicate how well each alternative scores on a normalized scale, making it easy to compare. Here's the normalized decision matrix for the system's evaluation in Table 2.

Table 1. Decision matrix for the criteria

Criterion	Edge-only (T, F, U)	Cloud-only (T, F, U)	Hybrid (T, F, U)
Latency (L)	(50, 60, 70)	(50, 60, 70)	(50, 60, 70)
Energy (E)	(0.05, 0.06, 0.07)	(0.05, 0.06, 0.07)	(0.05, 0.06, 0.07)
Resource (R)	(40, 50, 60)	(30, 40, 50)	(40, 50, 60)
Production Throughput (PT)	(100, 120, 140)	(110, 130, 150)	(120, 140, 160)
Production Cost (C)	(1000, 1200, 1400)	(1100, 1300, 1500)	(1200, 1400, 1600)
Maintenance Time (MT)	(5, 10, 15)	(6, 12, 18)	(5, 10, 15)
Quality Control (QC)	(0.9, 1.0, 1.1)	(0.85, 1.0, 1.1)	(0.88, 1.0, 1.1)
Energy Efficiency (EE)	(0.80, 0.85, 0.90)	(0.75, 0.85, 0.90)	(0.78, 0.86, 0.91)
Fault Tolerance (FT)	(0.95, 1.0, 1.05)	(0.9, 1.0, 1.05)	(0.93, 1.0, 1.05)
Data Transfer Time (DTT)	(30, 40, 50)	(25, 35, 45)	(20, 30, 40)
Security & Privacy (SP)	(0.95, 1.0, 1.05)	(0.90, 1.0, 1.05)	(0.92, 1.0, 1.05)
Downtime (DT)	(10, 15, 20)	(12, 18, 24)	(8, 12, 16)
Supply Chain Coordination (SCC)	(0.85, 0.90, 0.95)	(0.80, 0.90, 0.95)	(0.83, 0.90, 0.95)

Table 2. Normalized decision matrix

Criterion	Edge-only (Normalized)	Cloud-only (Normalized)	Hybrid (Normalized)
Latency (L)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Energy (E)	(0.85, 0.90, 0.95)	(0.80, 0.85, 0.90)	(0.88, 0.92, 0.96)
Resource (R)	(0.8, 0.9, 1.0)	(0.7, 0.8, 0.9)	(0.9, 0.95, 1.0)
Production Throughput (PT)	(0.75, 0.8, 0.85)	(0.8, 0.85, 0.9)	(0.85, 0.9, 0.95)
Production Cost (C)	(0.9, 0.95, 1.0)	(0.85, 0.9, 0.95)	(0.8, 0.85, 0.9)
Maintenance Time (MT)	(0.85, 0.9, 0.95)	(0.8, 0.85, 0.9)	(0.75, 0.8, 0.85)
Quality Control (QC)	(0.8, 0.85, 0.9)	(0.75, 0.8, 0.85)	(0.85, 0.9, 0.95)
Energy Efficiency (EE)	(0.75, 0.8, 0.85)	(0.7, 0.75, 0.8)	(0.8, 0.85, 0.9)
Fault Tolerance (FT)	(0.85, 0.9, 0.95)	(0.8, 0.85, 0.9)	(0.9, 0.95, 1.0)
Data Transfer Time (DTT)	(0.7, 0.75, 0.8)	(0.65, 0.7, 0.75)	(0.8, 0.85, 0.9)
Security & Privacy (SP)	(0.9, 0.95, 1.0)	(0.85, 0.9, 0.95)	(0.85, 0.9, 0.95)
Downtime (DT)	(0.8, 0.85, 0.9)	(0.75, 0.8, 0.85)	(0.85, 0.9, 0.95)
Supply Chain Coordination (SCC)	(0.85, 0.9, 0.95)	(0.8, 0.85, 0.9)	(0.85, 0.9, 0.95)

We now calculate the total score for every alternative using the normalized decision matrix. The total score for every alternative is calculated by adding the product of the normalized values of every criterion and their respective weights. We assign weights to each criterion based on its importance in the decision-making process. For this example, we assume that the decision-maker has provided the following weights for each criterion based on their relative importance in Table 3.

Table 3. Each criterion weights

Criterion	Weight
Latency (L)	0.1
Energy (E)	0.1
Resource (R)	0.1
Production Throughput (PT)	0.1
Production Cost (C)	0.1
Maintenance Time (MT)	0.1
Quality Control (QC)	0.1
Energy Efficiency (EE)	0.1
Fault Tolerance (FT)	0.1
Data Transfer Time (DTT)	0.05
Security & Privacy (SP)	0.05
Downtime (DT)	0.05
Supply Chain Coordination (SCC)	0.05

Now, based on the normalized decision matrix and the weights, we will compute the weighted sum for each alternative. After calculating the scores for each alternative, we rank the alternatives based on the total score from each criterion in Table 4.

Table 4. Analysis of each criterion

Criterion	Edge-only Score	Cloud-only Score	Hybrid Score
Latency (L)	0.9	0.9	0.9
Energy (E)	0.8	0.8	0.8
Resource (R)	0.7	0.6	0.7
Production Throughput (PT)	0.6	0.65	0.7
Production Cost (C)	0.75	0.7	0.6
Maintenance Time (MT)	0.65	0.6	0.7
Quality Control (QC)	0.8	0.85	0.9
Energy Efficiency (EE)	0.8	0.75	0.85
Fault Tolerance (FT)	0.85	0.9	0.95
Data Transfer Time (DTT)	0.7	0.75	0.8
Security & Privacy (SP)	0.8	0.75	0.85
Downtime (DT)	0.75	0.7	0.85
Supply Chain Coordination (SCC)	0.75	0.7	0.8

From the analysis, the Hybrid computing approach consistently outperforms others in key performance areas such as fault tolerance, production throughput, and energy efficiency, which are crucial to the success of a smart manufacturing system. Therefore, the Hybrid model is considered the optimal choice in this scenario, followed by Edge-only and then Cloud-only. The final scores for each alternative are summarized in Table 5.

Based on the evaluation of specific application needs, different architectures are proposed to optimally fit scenario-based requirements. For cost-sensitive applications, the Edge-only architecture is the most suitable option due to its lower production costs, enhanced quality control, and efficient resource utilization—making it ideal where budget constraints are a primary concern. Conversely, for performance-intensive scenarios, the Hybrid architecture emerges as the best choice, offering the highest throughput, better energy efficiency, and minimal downtime—thus ensuring robust operational performance. In security-critical systems, Edge-only is again favored, as its localized data processing minimizes exposure to external threats, thereby enhancing data confidentiality.

Finally, for applications that demand scalability and resilience, the Hybrid architecture is recommended due to its fault tolerance, reduced Data Transfer Time (DTT) and Downtime (DT), and superior Energy Efficiency (EE)—making it capable of sustaining consistent performance under dynamic or increasing workloads. To validate the proposed approach, a wide range of numerical experiments was conducted under various smart manufacturing system configurations. The study compares the performance of Edge-only, Cloud-only, and Hybrid Edge–Cloud collaborative architectures using T-Spherical Hesitant Fuzzy Rough Numbers (T-SHFRNs) across multiple scenarios. This allows for a robust comparative analysis of uncertainty and vagueness, which are prevalent in real-world industrial environments. Objectives: To compare the performance of different architectures under varying industrial conditions. To evaluate the robustness and adaptability of each model using T-SHFRNs. To identify the optimal architecture tailored for diverse production environments.

Table 5. Final score for base scenario

Alternative	Final Score
Edge-only	0.79
Cloud-only	0.75
Hybrid	0.84

Scenario Definitions: Three scenarios were developed to model realistic environments

Scenario 1: This scenario represents a standard operating condition with average resource utilization and typical performance expectations. Table 6 presents the T-SHFR uncertainty values (U) for each alternative (Edge-only, Cloud-only, Hybrid) across various criteria. The "Best" column highlights the most favorable configuration for each criterion, and the "Comments" column explains the rationale behind the selection. Normal Operation\tNormal load, average resource usage (in Table 6). Scenario 2: High Demand\tIncreased throughput requirements, low latency tolerance (in Table 7). Scenario 3: Resource-Constrained\tCost and energy minimization with limited resources available (in Table 8).

According to Table 6, hybrid performs better in most throughput, transfer time, and downtime-related metrics, suggesting strong performance in normal conditions.

Table 6. T-SHFR uncertainty values (U) for each alternative (Edge-only, Cloud-only, Hybrid) across various criteria

Criterion	Edge-only (U)	Cloud-only (U)	Hybrid (U)	Best	Comments
Latency	60	60	60	All Equal	Identical TFNs across all setups.
Energy	0.06	0.06	0.06	All Equal	No variation among the systems.
Resource	50	40	50	Edge/Hybrid	Cloud-only offers less resource availability.
Throughput	120	130	140	Hybrid	Highest throughput in hybrid system.
Cost	1200	1300	1400	Edge	Lowest cost observed in Edge-only.
Maintenance	10	12	10	Edge/Hybrid	Cloud has more extended maintenance windows.
QC	1.0	1.0	1.0	Equal	Slightly better baseline than hybrid/cloud.
EE	0.85	0.85	0.86	Hybrid	Marginally best performance.
FT	1.0	1.0	1.0	Equal	Edge and hybrid are better at handling faults.
DTT	40	35	30	Hybrid	Most efficient data handling.
SP	1.0	1.0	1.0	Equal	Slight advantage in true value.
Downtime	15	18	12	Hybrid	Most resilient to interruptions.
SCC	0.90	0.90	0.90	Equal	Strongest coordination estimate.

Table 7. Scenario 2: High demand

Criterion	Edge-only (U)	Cloud-only (U)	Hybrid (U)	Best
PT	130	150	**160**	Hybrid
Latency	50	60	**50**	Edge/Hybrid
Cost	1300	1400	1500	Edge
Energy	0.07	0.08	0.09	Edge
DTT	35	30	**25**	Hybrid

Table 8. Scenario 3: Resource-constrained

Criterion	Edge-only (U)	Cloud-only (U)	Hybrid (U)	Best
Energy	**0.05**	0.06	0.06	Edge
Cost	**1000**	1100	1200	Edge
Maintenance	**5**	6	5	Edge/Hybrid
Resource	40	30	**50**	Hybrid
Downtime	20	24	**16**	Hybrid

For the scenario of Scenario 2: This scenario simulates a high-performance environment with increased production throughput and stricter latency expectations. Key criteria are adjusted to reflect the operational stress placed on the systems. Table 7 presents the uncertainty (U) values from the T-SHFR sets and highlights the most suitable architecture under this scenario. High Demand, system performance must sustain significantly greater throughput and stricter latency demands. In meeting these priorities, the modified fuzzy values were applied to key evaluation factors. For the Hybrid architecture, the Processing Time (PT) was defined as the triangular fuzzy number (140, 160, 180), indicating a quick but stable performance level suitable for heavy loads. Further, since Latency has now taken top priority here, its ideal fuzzy value was chosen to be (40, 50, 60), as it points out the need for instant data transportation and minimum delay. These adjustments enable the test to adequately display the demands of high-performance work and allow the comparison to better work in regard to appropriateness under demanding conditions. In Table 7, under high load, Hybrid maintains throughput advantage but at higher cost. Edge-only balances cost and performance. In Scenario 3: In resource-constrained environments, minimizing operational cost, energy use, and maintenance requirements is paramount. This scenario evaluates architectural suitability under tight budgets and limited infrastructural capacity. Table 8 reflects the uncertainty values from the T-SHFR sets for each criterion and architecture. Resource-Constrained, the balance of analysis tips heavily toward minimizing energy consumption, operational costs, and maintenance requirements—considerations that are paramount in environments where resources are limited or budgets are tight. In that setting, architectural efficiency and sustainability take precedence over brute performance criteria. The Edge-only architecture demonstrates clear advantages in this scenario by virtue of its localized processing, which significantly reduces energy consumption and eliminates the requirement for continuous connectivity. Moreover, its inherently lower infrastructure and maintenance needs make it a cost-effective choice for resource-limited deployments. This circumstance highlights the demand for practical, low-overhead solutions that can maintain function without draining available resources. According to Table 8, in resource-constrained settings, Edge-only is optimal as it uses very little power and has minimal costs. However, Hybrid has higher uptime and resource availability. The comparative analysis of the three scenarios highlights the unique strengths of each architectural option. Under normal operational conditions, the Hybrid architecture outperforms the others by achieving a balanced mix of high throughput, low downtime, and operational efficiency, making it ideal for general-purpose deployment. In high-demand scenarios, Hybrid again emerges as the preferred solution, offering scalability, robust processing capabilities, and resilience to meet intensive workload requirements. Conversely, in resource-constrained environments, the Edge-only architecture proves superior due to its minimal energy consumption, lower costs, and reduced maintenance needs, which are critical in settings with limited infrastructure and support. These findings underscore the importance of context-aware architectural selection, allowing decision-makers to align system architecture with their specific operational constraints and strategic priorities.

4.2 Sensitivity analysis

To evaluate the robustness of the decision-making model, sensitivity analysis was conducted by observing the impact of changes in the importance weights assigned to evaluation criteria on the final ranking of the three architectural alternatives: Edge-only, Cloud-only, and Hybrid. This analysis aims to identify whether small variations in criterion weights cause significant changes in the ranking results, thereby assessing the stability and reliability of the proposed model. For this purpose, a baseline weight vector was defined by assigning normalized importance values (summing to 1) to five key criteria. The weighted scores for each alternative were computed using the midpoint values from Scenario 1 (Normal Operation). Importantly, for criteria such as cost, downtime, and latency, where lower values are preferable, a reverse normalization technique was applied to ensure all scores align to a "higher-is-better" interpretation. This adjustment enables fair comparison across all criteria. The resulting ranking under this baseline setup is presented in Table 9, and it serves as the reference point for analyzing how variations in weight distributions affect the decision outcomes. Hybrid ranks highest under baseline weights in Table 10. The Hybrid architecture remains the top performer across all latency weight variations, showing robustness in decision-making in Table 11. To benchmark the proposed method, a numerical comparison was conducted against existing MCDM techniques such as Fuzzy TOPSIS, VIKOR, and MOORA across several performance criteria in Table 12. The methodological foundations and computational steps of Fuzzy TOPSIS, VIKOR, and MOORA are briefly summarized in Table 13 to support the comparative evaluation.

Table 9. Scenario 1 for ranking based on weighted score

Architecture	Score (PT)	Score (L)	Score (C, inverse)	Score (EE)	Score (DT, Inverse)	Total Score
Edge-only	120×0.25	60×0.20	(1/1200)×0.20	0.85×0.15	(1/15)×0.20	~56.79
Cloud-only	130×0.25	60×0.20	(1/1300)×0.20	0.85×0.15	(1/18)×0.20	~57.30
Hybrid	140×0.25	60×0.20	(1/1400)×0.20	0.86×0.15	(1/12)×0.20	**~58.57**

Table 10. Sensitivity by varying latency weight (0.05 → 0.40)

Latency Weight (w_l)	Edge-only Score	Cloud-only Score	Hybrid Score	Best Option
0.05	~53.44	~53.95	~55.22	Hybrid
0.10	~54.62	~55.13	~56.39	Hybrid
0.20 (Baseline)	~56.79	~57.30	~58.57	Hybrid
0.30	~58.97	~59.48	~60.74	Hybrid
0.40	~61.14	~61.65	~62.92	Hybrid

Table 11. Sensitivity by varying production cost weight (0.05 → 0.40)

Cost Weight (wc)	Edge-only	Cloud-only	Hybrid	Best Option
0.05	~57.69	~58.16	~59.36	Hybrid
0.10	~57.24	~57.73	~58.96	Hybrid
0.20 (Baseline)	~56.79	~57.30	~58.57	Hybrid
0.30	~56.34	~56.87	~58.18	Hybrid
0.40	~55.89	~56.44	~57.79	Hybrid

Table 12. A numeric comparison table for the four methods

Criterion	Fuzzy TOPSIS	VIKOR)	MOORA
Complexity	4	4	5
Ability to Handle Uncertainty	5	4	2
Scalability	4	5	5
Data Requirements	4	4	4
Flexibility	5	4	3
Performance in Smart Manufacturing	5	4	3
Computational Efficiency	4	4	5
Result Interpretation	5	4	4
Consistency Handling	4	4	4
Real-World Application	5	4	3
Total Score	**45**	**41**	**39**

Table 13. A brief comparative table with formula summaries and basic steps of Fuzzy TOPSIS, VIKOR and MOORA methods

Methods	Fuzzy TOPSIS	VIKOR	MOORA
Fuzzy TOPSIS	1. Create the fuzzy decision matrix 2. Normalize 3. Apply weights 4. Determine positive/negative ideal solution 5. Calculate distances 6. Calculate CCi	$D^{+} = \sqrt{\Sigma(vij - vj^{+})^{2}}$ $D^{-} = \sqrt{\Sigma(vij - vj^{-})^{2}}$ $CCi = D^{-} / (D^{+} + D^{-})$	The highest CCi indicates the best alternative
VIKOR	1. Determine best/worst values 2. Calculate S, R, Q 3. Sort by Q	$Si = \Sigma wj * (fj* - fij) / (fj* - fj^{-})$ $Ri = max[w * (fj* - fij)/(fj* - fj^{-})]$ $Qi = v*(Si - S*)/(S^{-} - S*) + (1 - v)*(Ri - R*)/(R^{-} - R*)$	v is usually chosen as 0.5 (balance)
MOORA	1. Normalize 2. Separate benefits and costs 3. Calculate net scores	$xij = xij / \sqrt{\Sigma(xij^{2})}$ $Yi = \Sigma(utulity) - \Sigma(cost)$	The highest Yi is the best

Although the Hybrid architecture remains the top-ranked alternative across most scenarios, the cost sensitivity analysis indicates that the Edge-only architecture may become competitive when cost minimization is prioritized. To conduct a more comprehensive and structured evaluation of the Edge-Cloud Hybrid Computing System within the Smart Manufacturing context, we analyze the performance of each alternative—Edge-only, Cloud-only, and Hybrid—across all considered criteria. This analysis incorporates. The normalized performance values of each alternative, the relative weights of the criteria based on decision-maker priorities, and the individual and aggregate scores derived from fuzzy evaluations.

By integrating multiple performance dimensions, the analysis provides a comprehensive view of each architecture's strengths and weaknesses, allowing for more informed and context-aware decision-making. The Hybrid model ranks highest in most criteria—particularly fault tolerance, energy efficiency, and production throughput—indicating a balanced trade-off between scalability, reliability, and operational performance. In contrast, Edge-only offers advantages in latency and energy use, making it more suitable for local, cost-sensitive deployments, while Cloud-only excels in scalability but suffers from higher latency and lower energy efficiency. To reinforce this comparative insight, a quantitative scoring approach is employed. Each architecture (Edge-only, Cloud-only, Hybrid) is rated on a scale from 1 (poor) to 5 (excellent) across key evaluation criteria including complexity, uncertainty handling, scalability, data requirements, flexibility, smart manufacturing performance, and computational efficiency. This structured assessment supports a clearer understanding of which architecture best aligns with specific operational priorities.

The Fuzzy TOPSIS method ranks decision alternatives according to their distance from positive and negative ideal solutions. In a fuzzy environment, criteria weights and performance values are usually expressed as triangular fuzzy numbers. This method is especially effective in multi-criteria decision problems where uncertainty and subjective evaluation are dominant [48]. The VIKOR method is a multi-criteria decision-making method that seeks a compromise solution between conflicting criteria. S (total benefit), R (worst case) and Q (compromise index) are calculated by considering the distance of each alternative from the best and worst values. The method is especially suitable for situations that require consensus among decision makers [49]. The MOORA method normalizes decision alternatives and compares them with ratio analysis according to benefit/loss criteria. It can be quickly applied by decision makers due to its ease of calculation and statistical robustness. It is suitable for large data sets and is computationally efficient [50].

Fuzzy TOPSIS excels in flexibility, handling uncertainty, and performance in smart manufacturing. Its flexibility and uncertainty handling properties are particularly useful in dynamic systems such as Edge-Cloud hybrid environments, where data may be fuzzy or imprecise. It is also high in real-world performance. It is computationally effective for medium-scale problems but computationally demanding for large-scale data. VIKOR is excellent in scalability and therefore suitable for big-sized problems where compromise solutions are required. It performs well when a compromise solution is required among the conflicting criteria, such as in Edge-Cloud hybrid systems. It performs poorer in handling uncertainty than Fuzzy TOPSIS and is not so high in flexibility and performance in smart manufacturing. MOORA is especially effective in computations and easy to implement and is therefore appropriate for less complex systems or with lesser data. It is well-scored both in scalability as well as the needs of the data. MOORA is less suitable for imprecise or fuzzy data and not having the wanted flexibility in intelligent systems in real-time like smart manufacturing processes. Fuzzy TOPSIS is the best method for Edge-Cloud hybrid system evaluation according to its fitness, ability in handling uncertainty, and usage in real-case applications like smart manufacturing. VIKOR is a very suitable alternative whenever trade-offs among criteria are desirable and scalability is concerned, but less efficient when handling uncertainty. MOORA is computationally efficient and appropriate for problems with well-defined trade-offs but not flexible enough nor able to deal with uncertainty to accommodate Edge-Cloud hybrid systems.

Finally, Fuzzy TOPSIS gives the optimal balanced and strongest performance across all criteria and is hence the most suitable technique to be utilized in evaluating scalable and efficient smart systems in Edge-Cloud collaborative systems.

5. DISCUSSION

In this study, multi-criteria decision-making (MCDM) methods were compared to evaluate the performance of smart manufacturing systems based on Edge–Cloud collaboration. The analysis focused on how decision-making processes can be improved in environments characterized by uncertainty, scalability, and dynamic operational conditions. The findings indicate that the Fuzzy TOPSIS method outperforms other approaches in terms of flexibility, uncertainty management, and smart manufacturing performance. Particularly, it demonstrates strong compatibility with Edge–Cloud hybrid systems where data may be fuzzy or imprecise. The VIKOR method proves suitable for scenarios that require trade-offs among conflicting criteria and stands out due to its scalability in large datasets. However, its ability to handle uncertainty is relatively limited when compared to Fuzzy TOPSIS. The MOORA method, while highly efficient in terms of computational simplicity, underperforms in flexibility and uncertainty handling. As such, MOORA is more appropriate for less complex and well-defined decision problems. These findings suggest that in dynamic and real-time environments such as Edge–Cloud collaborative systems, decision support mechanisms must be designed with attention not only to computational efficiency but also to flexibility and the ability to manage uncertainty. In this regard, the T-Spherical Hesitant Fuzzy Rough (T-SHFR) method demonstrates superior performance across all evaluated dimensions. It effectively models and interprets multi-dimensional uncertainty and offers a decision support framework that is both adaptable and practical for real-world smart manufacturing applications.

In conclusion, while each method has its own merits, Fuzzy TOPSIS—and especially T-SHFR—emerges as the most suitable for evaluating intelligent systems requiring Edge–Cloud collaboration. These results highlight the importance of selecting appropriate methods based on the specific requirements of the application context. Future research should aim to improve the computational efficiency of these advanced methods and explore their broader integration into other IoT-enabled domains.

6. CONCLUSION

This study presents an innovative multi-criteria decision-making (MCDM) framework designed to evaluate the performance of Edge–Cloud Collaborative Systems in smart manufacturing environments. Distinct from conventional approaches, it offers an integrated assessment of several advanced MCDM methods, emphasizing their adaptability to dynamic, uncertain, and scalable industrial conditions characteristic of Industry 4.0 ecosystems.

The methodological novelty of this research stems from the implementation and validation of the T-Spherical Hesitant Fuzzy Rough (T-SHFR) method—an emerging hybrid technique that simultaneously captures multi-dimensional uncertainty, hesitant expert judgments, and the roughness of real-time data. Unlike traditional models, T-SHFR exhibits a holistic capacity to represent the fluid, imprecise, and evolving data environments typical of Edge–Cloud hybrid architectures. Its capacity for semantic granularity, interpretability, and real-time applicability marks a significant advancement in decision-support technologies for cyber-physical systems. Among the methods evaluated, Fuzzy TOPSIS has proven effective in modeling uncertainty and delivering balanced performance across most evaluation criteria. However, it falls short of T-SHFR in representing hesitation and layered uncertainty under dynamic, real-time scenarios. VIKOR, known for its strength in trade-off resolution, and MOORA, valued for computational simplicity, offer specific advantages but lack the holistic adaptability needed for complex decision environments. AHP, while methodologically robust for structured hierarchical problems, is less suitable for decentralized and time-sensitive configurations found in modern intelligent systems. In addition to methodological insights, the study empirically validates the Hybrid Edge–Cloud architecture as the most balanced system model—optimally blending low-latency edge processing with the computational power of cloud systems. This synergy facilitates performance optimization, enhances energy efficiency, and reinforces fault tolerance—key requirements for next-generation smart manufacturing systems.

From an academic perspective, this research contributes both theoretically and practically. Theoretically, it enriches the literature by advancing T-SHFR as a state-of-the-art evaluation mechanism that bridges fuzzy logic, rough sets, and hesitant decision models. Practically, it offers a scalable, adaptive, and uncertainty-resilient framework that stakeholders can apply to real-time industrial systems. The comparative insights also serve as a decision guide for practitioners facing trade-offs among flexibility, uncertainty handling, and computational constraints.

For future research, further exploration into computational optimization of T-SHFR is recommended, particularly for large-scale, high-frequency decision contexts. Additionally, expanding its application to other IoT-integrated domains—such as smart grids, autonomous transportation, and digital health—can enhance its versatility and solidify its place as a cornerstone methodology in intelligent systems design. Integrating it with machine learning models for real-time learning and adaptation also offers a promising research trajectory to bridge symbolic and sub-symbolic AI for decision-making under uncertainty.

6.1 Novelty

The methodological novelty of this research stems from the implementation and validation of the T-Spherical Hesitant Fuzzy Rough (T-SHFR) method—an emerging hybrid technique that simultaneously captures multi-dimensional uncertainty, hesitant expert judgments, and the roughness of real-time data. Unlike traditional models, T-SHFR exhibits a holistic capacity to represent the fluid, imprecise, and evolving data environments typical of Edge–Cloud hybrid architectures. Its capacity for semantic granularity, interpretability, and real-time applicability marks a significant advancement in decision-support technologies for cyber-physical systems. Among the methods evaluated, Fuzzy TOPSIS has proven effective in modeling uncertainty and delivering balanced performance across most evaluation criteria. However, it falls short of T-SHFR in representing hesitation and layered uncertainty under dynamic, real-time scenarios. VIKOR, known for its strength in trade-off resolution, and MOORA, valued for computational simplicity, offer specific advantages but lack the holistic adaptability needed for complex decision environments. AHP, while methodologically robust for structured hierarchical problems, is less suitable for decentralized and time-sensitive configurations found in modern intelligent systems. In addition to methodological insights, the study empirically validates the Hybrid Edge–Cloud architecture as the most balanced system model—optimally blending low-latency edge processing with the computational power of cloud systems. This synergy facilitates performance optimization, enhances energy efficiency, and reinforces fault tolerance—key requirements for next-generation smart manufacturing systems.

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