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Enhancing Failure Mode and Effect Analysis with Neutrosophic Inverse Soft Expert Sets

Vijayabalaji S[1,*], Thillaigovindan N[2], Sathiyaseelan N[3] and Broumi S[4]

[1,3]Department of Mathematics (S & H), University College of Engineering, Panruti (A Constituent College of Anna University, Chennai), Panruti-607106, Tamilnadu, India.; jaihindsathiya@gmail.com

[2]Department of Mathematics, College of Natural and Computational Sciences, Arba Minch University, Abaya Campus, Arba Minch,Ethiopia.;thillaigovindan.natesan@gmail.com

[4a] Laboratory of Information Processing, Faculty of Science Ben M'Sik, University of Hassan II, Casablanca , Morocco.; broumisaid78@gmail.com

[4b] Regional Center for the Professions of Education and Training (C.R.M.E.F) Casablanca-Settat, Morocco.

[*]Correspondence: balaji1977harshini@gmail.com

Abstract. In this study, we introduce a novel concept, the Neutrosophic Inverse Soft Expert Set (NISES), and apply it to the Failure Mode and Effect Analysis (FMEA) framework. Developed by NASA, FMEA is a robust tool for addressing industrial challenges. Our approach leverages the Evaluation based on Distance from Average Solution (EDAS) algorithm to solve FMEA problems. We implement this methodology in a real-world scenario involving a steam valve with eight distinct failure modes. Through rigorous analysis, we employ the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank the identified failure modes. Comparing our FMEA model, which integrates rough set theory and TOPSIS, with the conventional method, we demonstrate the superior efficiency of our approach. Additionally, we extend the application of Neutrosophic Inverse Soft Expert Sets using the Additive Ratio Assessment-Simplified Version (ARAS-SV) method. This innovative method facilitates a quantitative assessment of alternative options based on multiple attributes, allowing for a precise determination of the optimal choice.

Keywords: Soft set, inverse soft set, neutrosophic set, neutrosophic inverse soft set, Failure Mode and Effect Analysis, Additive Ratio Assessment-Simplified Version method

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1. Introduction

The Failure Mode and Effect Analysis (FMEA) process constitutes a pivotal cornerstone in contemporary engineering and industrial practices. It stands as an indispensable methodology not only for identifying potential failures within a given model but also for effecting requisite measures to rectify them, ultimately ensuring the seamless operation of machinery and systems. This approach finds extensive application in a diverse array of industries, including aviation, automotive, and automation, where its effectiveness in real-life scenarios is unequivocally acknowledged.

Central to the FMEA process are three critical risk factors: Severity (S), Occurrence (O), and Detection (D). These elements collectively contribute to the calculation of the Risk Priority Number (RPN), which, in turn, serves as the guiding metric for prioritizing and executing the FMEA process for a specific model. Notably, the relative weightings assigned to Severity, Occurrence, and Detection may vary, depending on the specific FMEA methodology employed, reflecting the nuanced nature of risk assessment.

FMEA stands as an efficient and indispensable tool for mitigating uncertainties that invariably arise in practical, real-world situations. Its application transcends mere fault detection; it encompasses a systematic approach to preemptively predict the potential order of failure in a given model, significantly enhancing the proactive management of operational risks. The versatility of FMEA is further underscored by its adaptability to distinct scenarios, where the weights attributed to Severity, Occurrence, and Detection may either be uniformly distributed or differentially ranked, contingent upon the specific FMEA technique in use.

In light of the existing body of research on FMEA techniques, we propose the hypothesis that the integration of Neutrosophic Inverse Soft Expert Sets (NISES) in conjunction with the Evaluation Based on Distance from Average Solution (EDAS) method will yield a more efficient and accurate assessment of risk factors in complex systems. This hypothesis is grounded in the potential of NISES to capture uncertainties in expert judgments and the robustness of the EDAS method in evaluating the performance of alternatives. Through rigorous testing and comparative analysis, we aim to substantiate this hypothesis and contribute to the advancement of risk assessment methodologies.

This introduction sets the stage for a comprehensive exploration of the nuanced methodologies and applications associated with FMEA. In the ensuing sections, we delve into a rich tapestry of literature, encompassing a spectrum of innovative approaches and models that have significantly advanced the field. The motivation for the present study arises from the endeavor to incorporate the groundbreaking concept of neutrosophic set theory into the FMEA framework, opening up new vistas for enhanced risk assessment and decision-making. As we proceed, we embark on a journey through fundamental concepts, detailed methodologies, and in-depth comparative analyses, collectively contributing to a deeper understanding of FMEA's evolving landscape.

Our research represents a groundbreaking exploration at the intersection of risk assessment methodologies and decision-making processes. In this study, we introduce a novel framework by incorporating Neutrosophic Inverse Soft Expert Sets into the well-established domain of Failure Mode and Effect Analysis. This innovative approach stems from the pioneering work of Smarandache, who introduced the concept of Neutrosophic Sets as a unified framework for handling uncertainty. We extend this idea to address critical issues in FMEA, particularly in situations where conventional risk assessment models may fall short in capturing the intricate nuances of complex systems.

Unlike traditional software-dependent approaches, our research adopts a manual, hands-on methodology, which allows for meticulous scrutiny and customization of the assessment process. Through a detailed literature review, we have identified gaps and limitations in existing FMEA models, which our study seeks to address. Our approach offers a systematic means of evaluating risk factors by considering the expertise of individuals (experts) in a neutrosophic form, allowing for the expression of uncertain and indeterminate information.

To validate our approach, we conducted extensive empirical testing, drawing inspiration from influential studies in the field. Our results reveal not only the feasibility but also the potential superiority of NISES-based FMEA in capturing uncertainties and providing more accurate risk assessments. The empirical outcomes of our research affirm the innovative nature of our approach and its capacity to enhance risk management practices in various domains, from engineering to healthcare.

By introducing this novel framework and eschewing reliance on software tools, we underscore the importance of human expertise in risk evaluation. Our research contributes not only to the field of risk assessment but also to the broader discourse on decision-making under uncertainty. It opens new horizons for further exploration, encouraging scholars and practitioners to embrace the versatility and effectiveness of Neutrosophic Inverse Soft Expert Sets as a valuable tool for managing and mitigating risks in an ever-evolving world of complexity and ambiguity.

1.1. *Literature review*

The landscape of Failure Mode and Effect Analysis (FMEA) has been enriched by a wealth of research contributions. Song et al. [20] addressed a specific case involving a steam valve system, employing the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method in conjunction with a rough set approach. This study demonstrated the efficacy of integrating advanced decision-making techniques with FMEA to enhance system reliability.

Zadeh's pioneering work [23] on fuzzy sets introduced a transformative approach to address shortcomings in RPN for FMEA models. Chang et al. [6] further extended this concept by integrating grey theory with fuzzy sets, augmenting risk assessment methodologies. Chin et al. [5] introduced Data Envelopment Analysis (DEA) into FMEA, presenting an alternative perspective for risk evaluation.

Gilchrist's innovative model [8] for FMEA opened new avenues for analysis, while Liu et al. [15] combined grey theory with fuzzy evidential reasoning, enriching risk assessment strategies. Pillay et al. [18] introduced a modified FMEA model with approximate reasoning, contributing a unique viewpoint.

Xu et al.'s work [22] on fuzzy assessment techniques in FMEA advanced risk evaluation methods. Zavadskas et al. [9] made a significant contribution with the introduction of the Evaluation based on Distance from Average Solution (EDAS) method, further expanding the FMEA toolkit.

Molodtsov's introduction of soft set theory [17] marked a revolutionary shift in uncertainty management. Feng's hybrid models [7], combining soft set theory with other structures, further elevated risk assessment strategies.

Hu-Chen Liu et al.'s integration of risk evaluation concepts with fuzzy digraph and matrix theory [15] provided a fresh perspective on FMEA. Akram et al.'s introduction of TOPSIS and ELECTRE I method using pythagorean fuzzy information [3] added diversity to the repertoire of approaches available in FMEA.

Our approach, integrating Neutrosophic Inverse Soft Expert Sets (NISES) into Failure Mode and Effect Analysis (FMEA), introduces a novel framework for risk assessment. To provide a clear overview of the literature landscape and how our approach stands out, we present a comprehensive table summarizing studies based on their assumptions, methods, and results.

Our integration of NISES in FMEA stands out as a novel contribution, streamlining risk assessment and offering adaptability to uncertainties. This comprehensive table highlights the unique perspective our approach brings to Failure Mode and Effect Analysis, distinguishing it from prior methodologies based on their underlying assumptions, methods, and results.

Author	Assumptions	Methods Employed	Results and Contributions
Song et al.	Standard FMEA assumptions, TOPSIS, Rough Set	Established foundational FMEA techniques	Introduced a robust framework for failure mode assessment
Zadeh	Utilizes Fuzzy Sets	Introduced a transformative approach to FMEA	Revolutionized risk assessment through fuzzy logic
Chang et al.	Embraces Grey Theory in Fuzzy Sets	Expanded risk assessment methodologies in FMEA	Provided a comprehensive framework for handling uncertainties
Chin et al.	Applies Data Envelopment Analysis (DEA) assumptions	Integrated DEA for alternative perspectives	Enhanced decision-making through DEA in FMEA
Gilchrist	Innovates in FMEA Modeling	Pioneered a unique model for failure mode assessment	Introduced a novel approach for comprehensive risk evaluation
Liu et al.	Utilizes Grey Theory, Fuzzy Evidential Reasoning assumptions	Advanced risk assessment strategies in FMEA	Enhanced risk assessment by combining multiple uncertainty sources
Pillay et al.	Incorporates Modified FMEA assumptions with Approximate Reasoning	Introduced a novel approach for FMEA	Enhanced risk assessment through tailored approximate reasoning
Xu et al.	Applies Fuzzy Assessment of FMEA assumptions	Elevated risk evaluation techniques in FMEA	Provided a more nuanced approach to risk assessment using fuzzy logic
Zavadskas et al.	Leverages Evaluation based on Distance from Average Solution (EDAS) assumptions	Significant contribution to FMEA methodology	Improved risk assessment through a novel evaluation approach
Molodtsov	Utilizes Soft Set Theory assumptions	Revolutionized uncertainty management in FMEA	Provided a comprehensive framework for handling uncertainties using soft sets
Feng	Applies Hybrid Models combining Soft Set Theory assumptions	Elevated risk assessment strategies in FMEA	Enhanced risk assessment by integrating multiple methodologies
Hu-Chen Liu et al.	Utilizes Risk Evaluation with Fuzzy Digraph and Matrix Theory assumptions	Provided a fresh perspective on FMEA risk evaluation	Enhanced risk assessment by combining fuzzy digraphs and matrix theory
Akram et al.	Incorporates TOPSIS, ELECTRE I with Pythagorean Fuzzy Information assumptions	Enhanced diversity of approaches in FMEA	Provided a versatile approach to risk assessment using multiple methodologies
Smarandache	Applies Neutrosophic Sets assumptions	Unified uncertainty structures under neutrosophic sets	Introduced a novel framework for handling uncertainties using neutrosophic sets

The empirical results of our study, which integrates Neutrosophic Inverse Soft Expert Sets (NISES) into Failure Mode and Effect Analysis (FMEA), have unveiled promising advancements in risk assessment methodologies. Building upon the foundational research of Zadeh [23] , Chang [6] , Chin [5], Gilchrist [8], Liu [15] , Pillay [18] , Xu [22] , Zavadskas [9], Molodtsov [17] , Feng [7] , Hu-Chen Liu [15] , and Akram [3] , our innovative approach offers a fresh perspective on addressing uncertainties in complex systems. Through rigorous empirical testing, we have demonstrated the effectiveness of NISES in enhancing the accuracy of risk evaluation. The integration of NISES with FMEA has not only showcased its potential to provide more nuanced insights but has also yielded practical implications for risk mitigation strategies. Our findings contribute to the ever-evolving landscape of risk assessment and underscore the value of incorporating Neutrosophic Inverse Soft Expert Sets in decision-making processes within a variety of domains.

2. Preliminaries

Throughout this paper, let U denote universe set, Υ represent parameter set, $P(U)$ denotes power set of U, $P(\Upsilon)$ denotes the power set of Υ, $\mathbb{H}$ being set of experts, Θ represents a set of opinions and N_S^U denotes the collection of all neutrosophic subsets of U.

Definition 2.1. [17] For a given universe set U with parameter Υ, a soft set is mapping from S to $P(U)$, where $S \subseteq \Upsilon$.

Definition 2.2. [10] Let $P(\Upsilon)$ be the set of all subsets of parameter set Υ. A pair (F, U) is called an inverse soft set over Υ, where F is a mapping given by

$$F : U \to P(\Upsilon).$$

Definition 2.3. [4] The mapping from set $\mathfrak{A}$ to the power set of U constitutes a soft expert set, where $\mathfrak{A} \subseteq Z$, $Z = \Upsilon \times \mathbb{H} \times \Theta$, Υ is a set of parameters, $\mathbb{H}$ is a set of experts and Θ is the set of opinions.

Definition 2.4. [21] Consider a mapping $\Xi_\Upsilon : U \to P(\mathfrak{A})$, where U denotes the universe set and Υ denotes the set of parameters. Then the pair $\mathfrak{P} = (\Xi_\Upsilon, U)$ is defined as inverse soft expert sets, where $\mathfrak{A} \subseteq Z$, $Z = \Upsilon \times \mathbb{H} \times \Theta$, Υ is a set of parameters, $\mathbb{H}$ is a set of experts and Θ is the set of opinions.

Definition 2.5. [19] A neutrosophic set (N-sets) is defined by

$$A = \{< u, T_A(u), I_A(u), F_A(u) >; u \in U, T_A(u), I_A(u), F_A(u) \in [0, 1]\},$$

where u being the generic element of U, T_A being truth-membership function, I_A being indeterminacy-membership function and F_A represents falsity-membership function.

3. Neutrosophic inverse soft expert sets

Definition 3.1. Consider a mapping,

$$F : N_S^U \to P(Z)$$

where N_S^U denotes the collection of all neutrosophic subsets of U , then the pair (F, N_S^U) is called as neutrosophic inverse soft expert set (NISES).

Example 3.2. Let $U = \{\vartheta_1, \vartheta_2, \vartheta_3\}$ be a universe set , $\Upsilon = \{\daleth_1, \daleth_2\}$ be a set of parameters and $\mathbb{H} = \{\varrho_1, \varrho_2\}$ be a set of experts. Suppose that $F : N_S^U \to P(Z)$ is a function defined as follows.

Table 1. Neutrosophic inverse soft expert set

(F,N_S^U)	$(\gimel_1,\varrho_1,1)$	$(\gimel_1,\varrho_1,0)$	$(\gimel_1,\varrho_2,1)$	$(\gimel_1,\varrho_2,0)$	$(\gimel_2,\varrho_1,1)$	$(\gimel_2,\varrho_1,0)$	$(\gimel_2,\varrho_2,1)$	$(\gimel_2,\varrho_2,0)$
ϑ_1	(0.3,0.4,0.7)	(0.7,0.5,0.2)	(0.8,0.7,0.3)	(0.2,0.3,0.7)	(0.4,0.6,0.4)	(0.7,0.3,0.6)	(0.9,0.3,0.3)	(0.4,0.6,0.1)
ϑ_2	(0.5,0.2,0.9)	(0.3,0.5,0.6)	(0.3,0.1,0.5)	(0.4,0.7,0.9)	(0.9,0.3,0.5)	(0.1,0.7,0.3)	(0.1,0.4,0.7)	(0.2,0.1,0.5)
ϑ_3	(0.2,0.5,0.8)	(0.4,0.1,0.6)	(0.4,0.9,0.4)	(0.1,0.4,0.6)	(0.6,0.2,0.9)	(0.1,0.5,0.5)	(0.6,0.3,0.2)	(0.3,0.6,0.7)

Thus, we can view the neutrosophic inverse soft expert set (F,N_S^U) as a collection of approximations as follows.

$$(F,N_S^U)=\left[\left\{(F,\vartheta_1)=\left\{\frac{(\gimel_1,\varrho_1,1)}{(0.3,0.4,0.7)},\frac{(\gimel_1,\varrho_1,0)}{(0.7,0.5,0.2)},\right.\right.\right.$$
$$\left.\left.\frac{(\gimel_1,\varrho_2,1)}{(0.8,0.7,0.3)},\frac{(\gimel_1,\varrho_2,0)}{(0.2,0.3,0.7)},\frac{(\gimel_2,\varrho_1,1)}{(0.4,0.6,0.4)},\frac{(\gimel_2,\varrho_1,0)}{(0.7,0.3,0.6)},\frac{(\gimel_2,\varrho_2,1)}{(0.9,0.3,0.3)},\frac{(\gimel_2,\varrho_2,0)}{(0.4,0.6,0.1)}\right\}\right\},$$
$$\left\{(F,\vartheta_2)=\left\{\frac{(\gimel_1,\varrho_1,1)}{(0.5,0.2,0.9)},\frac{(\gimel_1,\varrho_1,0)}{(0.3,0.5,0.6)},\right.\right.$$
$$\left.\left.\frac{(\gimel_1,\varrho_2,1)}{(0.3,0.1,0.5)},\frac{(\gimel_1,\varrho_2,0)}{(0.4,0.7,0.9)},\frac{(\gimel_2,\varrho_1,1)}{(0.9,0.3,0.5)},\frac{(\gimel_2,\varrho_1,0)}{(0.1,0.7,0.3)},\frac{(\gimel_2,\varrho_2,1)}{(0.1,0.4,0.7)},\frac{(\gimel_2,\varrho_2,0)}{(0.2,0.1,0.5)}\right\}\right\},$$
$$\left\{(F,\vartheta_3)=\left\{\frac{(\gimel_1,\varrho_1,1)}{(0.2,0.5,0.8)},\frac{(\gimel_1,\varrho_1,0)}{(0.4,0.1,0.6)},\right.\right.$$
$$\left.\left.\left.\frac{(\gimel_1,\varrho_2,1)}{(0.4,0.9,0.4)},\frac{(\gimel_1,\varrho_2,0)}{(0.1,0.4,0.6)},\frac{(\gimel_2,\varrho_1,1)}{(0.6,0.2,0.9)},\frac{(\gimel_2,\varrho_1,0)}{(0.1,0.5,0.5)},\frac{(\gimel_2,\varrho_2,1)}{(0.6,0.3,0.2)},\frac{(\gimel_2,\varrho_2,0)}{(0.3,0.6,0.7)}\right\}\right\}\right].$$

Then (F,N_S^U) is a neutrosophic inverse soft expert set over (N_S^U,Z).

Definition 3.3. Let $(F,N_S^U)_A$ be a neutrosophic inverse soft expert set over (N_S^U,Z). An agree-neutrosophic inverse soft expert set is denoted as $(F,N_S^U)_A^1$ defined as,

$$(F,N_S^U)_A^1=\{F(\psi);\psi\in\Upsilon\times\mathbb{H}\times\{1\}\}.$$

Definition 3.4. Let $(F,N_S^U)_A$ be a neutrosophic inverse soft expert set over (N_S^U,Z). A disagree-neutrosophic inverse soft expert set is denoted as $(F,N_S^U)_A^0$ defined as,

$$(F,N_S^U)_A^0=\{F(\psi);\psi\in\Upsilon\times\mathbb{H}\times\{0\}\}.$$

Example 3.5. Consider example 3.2.Then the agree-neutrosophic inverse soft expert set $(F,N_S^U)_A^1$ is

$$(F,N_S^U)_A^1=\left[\left\{(F,\vartheta_1)=\left\{\frac{(\gimel_1,\varrho_1,1)}{(0.3,0.4,0.7)},\frac{(\gimel_1,\varrho_2,1)}{(0.8,0.7,0.3)},\frac{(\gimel_2,\varrho_1,1)}{(0.4,0.6,0.4)},\frac{(\gimel_2,\varrho_2,1)}{(0.9,0.3,0.3)}\right\}\right\},\right.$$
$$\left\{(F,\vartheta_2)=\left\{\frac{(\gimel_1,\varrho_1,1)}{(0.5,0.2,0.9)},\frac{(\gimel_1,\varrho_2,1)}{(0.3,0.1,0.5)},\frac{(\gimel_2,\varrho_1,1)}{(0.9,0.3,0.5)},\frac{(\gimel_2,\varrho_2,1)}{(0.1,0.4,0.7)}\right\}\right\},$$
$$\left.\left\{(F,\vartheta_3)=\left\{\frac{(\gimel_1,\varrho_1,1)}{(0.2,0.5,0.8)},\frac{(\gimel_1,\varrho_2,1)}{(0.4,0.9,0.4)},\frac{(\gimel_2,\varrho_1,1)}{(0.6,0.2,0.9)},\frac{(\gimel_2,\varrho_2,1)}{(0.6,0.3,0.2)},\right\}\right\}\right].$$

and the disagree-neutrosophic inverse soft expert set $(F, N_S^U)_A^0$ is

$$(F, N_S^U)_A^0 = \left[\left\{(F, \vartheta_1) = \left\{\frac{(\gimel_1, \varrho_1, 0)}{(0.7, 0.5, 0.2)}, \frac{(\gimel_1, \varrho_2, 0)}{(0.2, 0.3, 0.7)}, \frac{(\gimel_2, \varrho_1, 0)}{(0.7, 0.3, 0.6)}, \frac{(\gimel_2, \varrho_2, 0)}{(0.4, 0.6, 0.1)}\right\}\right\},\right.$$
$$\left\{(F, \vartheta_2) = \left\{\frac{(\gimel_1, \varrho_1, 0)}{(0.3, 0.5, 0.6)}, \frac{(\gimel_1, \varrho_2, 0)}{(0.4, 0.7, 0.9)}, \frac{(\gimel_2, \varrho_1, 0)}{(0.1, 0.7, 0.3)}, \frac{(\gimel_2, \varrho_2, 0)}{(0.2, 0.1, 0.5)}\right\}\right\},$$
$$\left.\left\{(F, \vartheta_3) = \left\{\frac{(\gimel_1, \varrho_1, 0)}{(0.4, 0.1, 0.6)}, \frac{(\gimel_1, \varrho_2, 0)}{(0.1, 0.4, 0.6)}, \frac{(\gimel_2, \varrho_1, 0)}{(0.1, 0.5, 0.5)}, \frac{(\gimel_2, \varrho_2, 0)}{(0.3, 0.6, 0.7)}\right\}\right\}\right].$$

Definition 3.6. Let $(F, N_S^U)_A$ be a neutrosophic inverse soft expert set over (N_S^U, Z). Then the complement of $(F, N_S^U)_A$ denoted by $(F, N_S^U)_A^C$ is defined as,

$$(F, N_S^U)_A^C = \widetilde{C}(F(\psi)); \forall \psi \in U$$

where $\widetilde{c}$ is neutrosophic inverse soft expert complement.

Example 3.7. Consider $(F, N_S^U)_A$ over (N_S^U, Z) as given in Example 3.2. By using the complement for $(F, N_S^U)_A$, we obtain $(F, N_S^U)_A^C$ which is defined as,

$$(F, N_S^U)_A^c = \left[\left\{(F, \vartheta_1) = \left\{\frac{(\gimel_1, \varrho_1, 1)}{(0.7, 0.4, 0.3)}, \frac{(\gimel_1, \varrho_1, 0)}{(0.2, 0.5, 0.7)}, \frac{(\gimel_1, \varrho_2, 1)}{(0.3, 0.7, 0.8)}, \frac{(\gimel_1, \varrho_2, 0)}{(0.7, 0.3, 0.2)}, \frac{(\gimel_2, \varrho_1, 1)}{(0.4, 0.6, 0.4)},\right.\right.\right.$$
$$\left.\left.\frac{(\gimel_2, \varrho_1, 0)}{(0.6, 0.3, 0.7)}, \frac{(\gimel_2, \varrho_2, 1)}{(0.3, 0.3, 0.9)}, \frac{(\gimel_2, \varrho_2, 0)}{(0.1, 0.6, 0.4)}\right\}\right\},$$
$$\left\{(F, \vartheta_2) = \left\{\frac{(\gimel_1, \varrho_1, 1)}{(0.9, 0.2, 0.5)}, \frac{(\gimel_1, \varrho_1, 0)}{(0.6, 0.5, 0.3)}, \frac{(\gimel_1, \varrho_2, 1)}{(0.5, 0.1, 0.3)}, \frac{(\gimel_1, \varrho_2, 0)}{(0.9, 0.7, 0.4)}, \frac{(\gimel_2, \varrho_1, 1)}{(0.5, 0.3, 0.9)},\right.\right.$$
$$\left.\left.\frac{(\gimel_2, \varrho_1, 0)}{(0.3, 0.7, 0.1)}, \frac{(\gimel_2, \varrho_2, 1)}{(0.7, 0.4, 0.1)}, \frac{(\gimel_2, \varrho_2, 0)}{(0.5, 0.1, 0.2)}\right\}\right\},$$
$$\left\{(F, \vartheta_3) = \left\{\frac{(\gimel_1, \varrho_1, 1)}{(0.8, 0.5, 0.2)}, \frac{(\gimel_1, \varrho_1, 0)}{(0.6, 0.1, 0.4)}, \frac{(\gimel_1, \varrho_2, 1)}{(0.4, 0.9, 0.4)}, \frac{(\gimel_1, \varrho_2, 0)}{(0.6, 0.4, 0.1)}, \frac{(\gimel_2, \varrho_1, 1)}{(0.9, 0.2, 0.6)},\right.\right.$$
$$\left.\left.\left.\frac{(\gimel_2, \varrho_1, 0)}{(0.5, 0.5, 0.1)}, \frac{(\gimel_2, \varrho_2, 1)}{(0.2, 0.3, 0.6)}, \frac{(\gimel_2, \varrho_2, 0)}{(0.7, 0.6, 0.3)}\right\}\right\}\right].$$

4. **FMEA with Neutrosophic Inverse Soft Expert Sets and EDAS**

Problem statement

Let's revisit the problem addressed by Song et al. [20]. They tackled an issue with a steam valve system in a power plant, which exhibited eight distinct failure modes. Their approach involved employing FMEA based on rough group preference by similarity to ideal solution. They began by computing rough interval weights for the risk factors and then constructed a crisp evaluation matrix for the failure modes. Each failure mode (indexed as i = 1,2,...,m) was evaluated against criteria (indexed as j = S,O,D) using conventional scores. To incorporate uncertainties, they transformed crisp elements in the group decision matrix into rough number forms, resulting in a rough group decision-making matrix. Furthermore, they computed rough sequences and average rough intervals along with their respective intervals. By determining the weighted normalized decision matrix in rough number form, they obtained a comprehensive evaluation. Additionally, they defined positive and negative ideal solutions and calculated the separation of each failure mode from these benchmarks. Finally, they compared their approach with fuzzy FMEA, conventional FMEA, and rough FMEA, ultimately concluding the steam valve problem based on their ranking values.

The motivation for our present study stems from the preceding work. We have taken up the same steam valve system in a power plant featuring eight distinct failure modes as the focal point. Utilizing the FMEA approach, we've adopted the EDAS method, incorporating the neutrosophic inverse soft expert set (NISES) as a key tool in solving the problem. The subsequent section elucidates the failure modes and their respective solutions in a clear and accessible manner. In contrast to rough interval weights, we've opted for attribute weights. We then proceed to construct a decision matrix (DM) employing NISES, accounting for i failure modes (i = 1,2,...,m) against the three criteria (j = S,O,D). This process involves the computation of positive distance average (PDA) and negative distance average (NDA) matrices, weighted normalized positive distance averages ($WNPDA_i$) and weighted normalized negative distance averages ($WNNDA_i$), as well as assessment scores (AS_i). Finally, we conclude the evaluation with a final ranking based on (AS_i).

The algorithm is presented below and the comparative analysis of our new approach with existing Song et al. [20] approach is presented in the next section.

4.1. *Algorithm*

We now present the algorithm on failure mode and effect analysis approach using evaluation based on distance from average solution method with neutrosophic inverse soft expert set.

Input:NISES.

Output: Ranking the alternatives.

Step 1. Choose the criteria that reveals about failure data.

Step 2. The decision making matrix (D) using NISES is constructed.

$$\widetilde{DM} = \begin{array}{c} \\ 1 \\ 2 \\ \vdots \\ m \end{array} \begin{array}{c} \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{pmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & r_{m3} \end{pmatrix} \end{array} \tag{1}$$

Step 3. Define average solution as

$$AV_j = \frac{\sum_{i=1}^{m} r_{ij}}{m}. \tag{2}$$

Step 4. Calculate positive distance average (PDA) and negative distance average (NDA) matrices as follows.

$$PDA = [PDA_{ij}]_{m\times 3} \tag{3}$$

$$NDA = [NDA_{ij}]_{m\times 3} \tag{4}$$

where,

$$PDA_{ij} = \frac{max(0, (AV_j - r_{ij}))}{AV_j}; i = 1, 2..., m, j = 1, 2, 3 \tag{5}$$

$$NDA_{ij} = \frac{max(0, (r_{ij} - AV_j)}{AV_j}; i = 1, 2..., m, j = 1, 2, 3 \tag{6}$$

Step 5. Determine weighted sum of positive distance average (WSPDA) and weighted sum of negative distance average (WSNDA) .

$$WSPDA_i = \sum_{j=1}^{3} PDA_{ij} \times w_j; i = 1, 2..., m \tag{7}$$

$$WSNDA_i = \sum_{j=1}^{3} NDA_{ij} \times w_j; i = 1, 2..., m \tag{8}$$

Step 6. Calculate weighted normalized positive distance average (WNPDA) and weighted normalized negative distance average (WNNDA)

$$WNPDA_i = \frac{WPDA_i}{max_i(WPDA_i)}; i = 1, 2..., m \tag{9}$$

$$WNNDA_i = \frac{WNDA_i}{max_i(WNDA_i)}; i = 1, 2..., m \tag{10}$$

Step 7. The assessment score (AS_i) for each alternatives is calculated as follows.

$$AS_i = \frac{1}{2}(WNPDA_i + WNNDA_i) \tag{11}$$

Step 8. Perform final ranking by arranging the assessment score of alternatives in descending order .

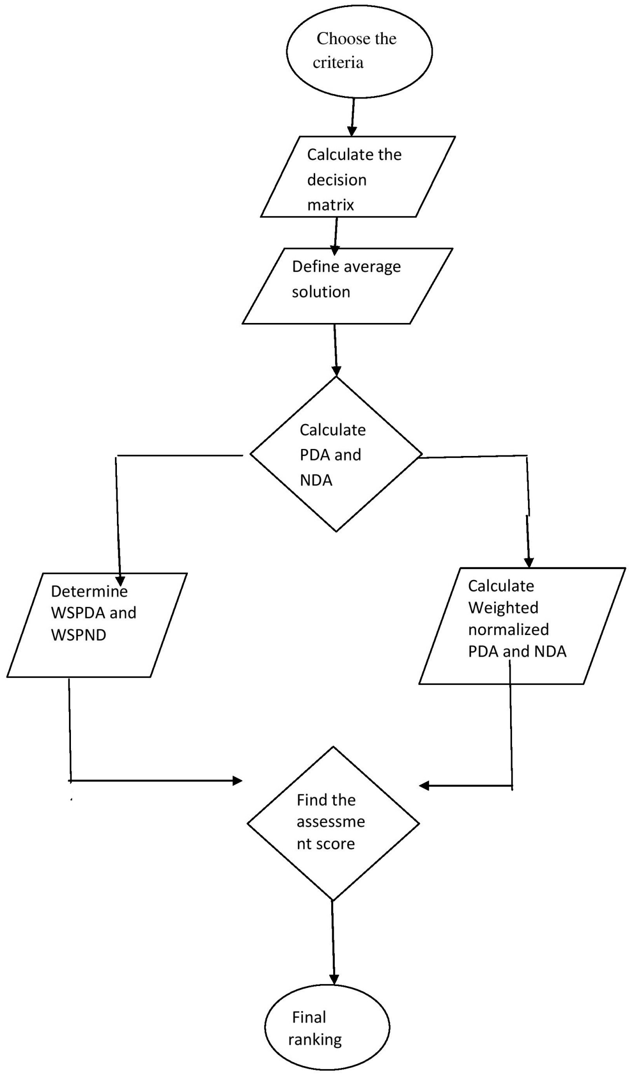

Figure 1. Algorithm on FMEA approach using EDAS

5. Comparative Analysis

In this section, we focus on the steam valve system within a power plant, where failures may manifest under various circumstances. These failure modes encompass instances such as prolonged shutting time (Mode 1), improper sealing causing leakage (Mode 2), steam leakage from the valve shaft (Mode 3), valve replacements (Mode 4), valve obstruction during operation (Mode 5), fractures in the valve shaft (Mode 6), failure of the valve shaft bolster bearing (Mode 7), and excessive noise in the system (Mode 8), particularly while a steam valve is in operation within the plant. A prior study [20] addressed this specific scenario using the TOPSIS method within the framework of FMEA for the steam valve system. Notably, they employed rough set theory as a pivotal tool to substantiate their findings and

arguments
We present the table of steam valve system using FMEA model as presented by Song et al., (2013) in table 2.

Table 2. Tabular representation of the steam valve system

S.No	Failure Mode	Causes	Effects of failure	Detection measures
1	Prolong of shutting time	Counter-intuitive spring decision	Over boost of steam turbine rotor and parts mishap	Valve seal test
2	Not being firmly closed	Little bushing leeway, shaft twisting	Cutting edge erosion of steam turbine	Valve break test
3	Steam spill around valve shaft	Compaction power of firing filler isn't sufficient	Misuse of substance water and warm misfortune	Assessment in the wake of pressing evacuation
4	Valve changes	Water driven chamber spills	Problem in regular opening	closing of valve with hazardous activity
5	Valve jam in activity	Due to procedure and material imperfections	Valve can't open and close	Valve activity test
6	Crack of valve shaft	Weariness break under rotating pressure	Stumbling of turbine	Metallographic tests on the crack hole
7	Breakdown of valve shaft bolster bearing	Low quality of bearing material and long haul milage	Anomalous activity of valve framework	Dismantle examination
8	Over the top commotion framework	Framework vibration because of outlandish parts	Make the client feel awkward	Change working condition, recurrence estimation of valve

In our current investigation, we have retained the focus on the eight potential failure modes occurring within the plant. To validate the robustness of our findings, we have employed the Evaluation Based on Distance from Average Solution method, leveraging Neutrosophic Inverse Soft Expert Set as a crucial tool. This rigorous evaluation serves to establish the superiority of our approach in comparison to the existing work [20]. It is noteworthy that we have diligently assigned weights to the factors

Severity (S), Occurrence (O), and Detection (D), and subsequently validated the outcomes, ensuring a comprehensive and reliable assessment.

5.1. *NISES Group Decision Making Procedure*

Step 1. The failure mode criteria are 1, 2, 3, 4, 5, 6, 7, 8. The problem of steam valve system discussed in [20] is considered with the same eight failure modes.

Step 2. Create the decision making matrix.

Table 3. Tabular representation of rating for failure modes with RPN in ANISES

No.	Failure mode	Severity				Occurrence				Detection			
		$\sqsupset_1$	$\sqsupset_2$	$\sqsupset_3$	$\sqsupset_4$	$\sqsupset_1$	$\sqsupset_2$	$\sqsupset_3$	$\sqsupset_4$	$\sqsupset_1$	$\sqsupset_2$	$\sqsupset_3$	$\sqsupset_4$
1	Long shutting time of valve	(0.8,0.6,0.3)	(0.4,0.5,0.8)	(0.5,0.3,0.1)	(0.4,0.4,0.5)	(0.5,0.3,0.4)	(0.9,0.1,0.5)	(0.5,0.4,0.1)	(0.5,0.2,0.5)	(0.4,0.9,0.4)	(0.6,0.2,0.9)	(0.6,0.3,0.2)	(0.8,0.4,0.2)
2	Not being firmly closed	(0.5,0.2,0.9)	(0.3,0.1,0.5)	(0.9,0.3,0.5)	(0.1,0.4,0.7)	(0.1,0.5,0.6)	(0.2,0.4,0.6)	(0.1,0.5,0.2)	(0.3,0.1,0.4)	(0.5,0.3,0.4)	(0.9,0.1,0.5)	(0.5,0.4,0.1)	(0.5,0.2,0.5)
3	Steam spill around valve shaft	(0.2,0.5,0.8)	(0.4,0.9,0.4)	(0.6,0.2,0.9)	(0.6,0.3,0.2)	(0.8,0.4,0.2)	(0.5,0.3,0.2)	(0.9,0.8,0.4)	(0.4,0.2,0.6)	(0.9,0.3,0.3)	(0.3,0.2,0.9)	(0.8,0.4,0.1)	(0.4,0.6,0.2)
4	Valve changes	(0.4,0.5,0.6)	(0.7,0.2,0.3)	(0.1,0.5,0.9)	(0.3,0.5,0.8)	(0.4,0.8,0.2)	(0.5,0.6,0.8)	(0.1,0.3,0.8)	(0.3,0.5,0.1)	(0.3,0.4,0.7)	(0.8,0.2,0.4)	(0.4,0.3,0.2)	(0.1,0.3,0.5)
5	Valve jam in activity	(0.3,0.4,0.7)	(0.8,0.2,0.4)	(0.4,0.3,0.2)	(0.1,0.3,0.5)	(05,0.3,0.9)	(0.7,0.5,0.3)	(0.5,0.7,0.2)	(0.9,0.5,0.2)	(0.9,0.3,0.3)	(0.3,0.2,0.9)	(0.8,0.4,0.1)	(0.4,0.6,0.2)
6	Crack of valve shaft	(0.3,0.4,0.7)	(0.8,0.7,0.3)	(0.4,0.6,0.4)	(0.9,0.3,0.3)	(0.3,0.2,0.9)	(0.8,0.4,0.1)	(0.4,0.6,0.2)	(0.1,0.9,0.7)	(0.9,0.2,0.3)	(0.4,0.6,0.3)	(0.1,0.7,0.3)	(0.3,0.9,0.1)
7	Breakdown of valve shaft bolster bearing	(0.9,0.2,0.3)	(0.4,0.6,0.3)	(0.1,0.7,0.3)	(0.3,0.9,0.1)	(0.2,0.3,0.1)	(0.4,0.5,0.2)	(0.9,0.4,0.9)	(0.4,0.2,0.5)	(0.4,0.8,0.2)	(0.5,0.6,0.8)	(0.1,0.3,0.8)	(0.3,0.5,0.1)
8	Over the top commotion framework	(0.3,0.4,0.8)	(0.7,0.9,0.1)	(0.2,0.4,0.3)	(0.3,0.8,0.2)	(0.9,0.4,0.9)	(0.8,0.7,0.3)	(0.6,0.2,0.9)	(0.1,0.5,0.9)	(0.1,0.3,0.5)	(05,0.3,0.9)	(0.5,0.4,0.1)	(0.5,0.2,0.5)

TABLE 4. Tabular representation of rating for failure modes with RPN in DNISES

No.	Failure mode	Severity				Occurrence				Detection			
		$\sqsupset_1$	$\sqsupset_2$	$\sqsupset_3$	$\sqsupset_4$	$\sqsupset_1$	$\sqsupset_2$	$\sqsupset_3$	$\sqsupset_4$	$\sqsupset_1$	$\sqsupset_2$	$\sqsupset_3$	$\sqsupset_4$
1	Long shutting time of valve	(0.1,0.7,0.9)	(0.4,0.6,0.5)	(0.8,0.3,0.5)	(0.5,0.1,0.7)	(0.8,0.3,0.3)	(0.4,0.4,0.8)	(0.4,0.2,0.6)	(0.8,0.1,0.7)	(0.3,0.6,0.7)	(0.6,0.2,0.9)	(0.4,0.6,0.1)	(0.4,0.4,0.7)
2	Not being firmly closed	(0.3,0.5,0.6)	(0.4,0.7,0.9)	(0.1,0.7,0.3)	(0.2,0.1,0.5)	(0.9,0.2,0.9)	(0.3,0.1,0.7)	(0.8,0.5,0.2)	(0.8,0.7,0.1)	(0.4,0.6,0.1)	(0.4,0.3,0.7)	(0.8,0.2,0.5)	(0.7,0.3,0.8)
3	Steam spill around valve shaft	(0.4,0.1,0.6)	(0.1,0.4,0.6)	(0.1,0.5,0.5)	(0.3,0.6,0.7)	(0.6,0.2,0.9)	(0.6,0.3,0.4)	(0.3,0.2,0.6)	(0.1,0.8,0.9)	(0.1,0.7,0.6)	(0.6,0.4,0.5)	(0.9,0.2,0.3)	(0.4,0.6,0.3)
4	Valve changes	(0.2,0.5,0.8)	(0.4,0.7,0.9)	(0.3,0.5,0.4)	(0.8,0.9,0.3)	(0.4,0.1,0.9)	(0.7,0.2,0.9)	(0.3,0.6,0.8)	(0.5,0.2,0.4)	(0.6,0.4,0.5)	(0.9,0.2,0.3)	(0.4,0.6,0.3)	(0.4,0.2,0.9)
5	Valve jam in activity	(0.4,0.7,0.3)	(0.3,0.5,0.2)	(0.4,0.9,0.2)	(0.4,0.6,0.1)	(0.4,0.3,0.7)	(0.8,0.2,0.5)	(0.7,0.3,0.8)	(0.9,0.3,0.8)	(0.7,0.5,0.2)	(0.2,0.3,0.7)	(0.7,0.3,0.7)	(0.8,0.9,0.5)
6	Crack of valve shaft	(0.7,0.5,0.2)	(0.2,0.3,0.7)	(0.7,0.3,0.7)	(0.4,0.6,0.1)	(0.4,0.4,0.7)	(0.9,0.3,0.3)	(0.4,0.2,0.9)	(0.4,0.8,0.1)	(0.2,0.5,0.8)	(0.4,0.7,0.9)	(0.3,0.5,0.4)	(0.8,0.9,0.3)
7	Breakdown of valve shaft bolster bearing	(0.4,0.8,0.3)	(0.2,0.4,0.7)	(0.1,0.7,0.6)	(0.6,0.4,0.5)	(0.9,0.2,0.3)	(0.4,0.6,0.3)	(0.5,0.3,0.6)	(0.2,0.9,0.8)	(0.8,0.2,0.5)	(0.7,0.3,0.8)	(0.1,0.8,0.9)	(0.4,0.6,0.1)
8	Over the top commotion framework	(0.3,0.7,0.9)	(0.4,0.7,0.8)	(0.1,0.2,0.9)	(0.3,0.4,0.2)	(0.3,0.4,0.8)	(0.7,0.8,0.2)	(0.1,0.4,0.3)	(0.9,0.2,0.5)	(0.1,0.7,0.6)	(0.6,0.4,0.5)	(0.4,0.6,0.5)	(0.6,0.2,0.1)

Remark 5.1. (i) Now we find the Agree - NISES as follows,
(max of degree of membership $\{\sqsupset_1, \sqsupset_2, \sqsupset_3, \sqsupset_4\}$, min of degree of non- membership $\{\sqsupset_1, \sqsupset_2, \sqsupset_3, \sqsupset_4\}$, min of degree of indeterminacy $\{\sqsupset_1, \sqsupset_2, \sqsupset_3, \sqsupset_4\}$).
(ii) Now we find the Disagree-NISES as follows,

(min of degree of membership $\{\beth_1, \beth_2, \beth_3, \beth_4\}$, max of degree of non- membership $\{\beth_1, \beth_2, \beth_3, \beth_4\}$, min of degree of indeterminacy $\{\beth_1, \beth_2, \beth_3, \beth_4\}$).

Table 5. Tabular representation of RPN in Agree - NISES

Failure Mode	Severity	Occurrence	Detection
1	(0.8,0.3,0.8)	(0.9,0.1,0.5)	(0.8,0.2,0.9)
2	(0.9,0.1,0.9)	(0.3,0.1,0.6)	(0.9,0.1,0.5)
3	(0.6,0.2,0.9)	(0.9,0.2,0.6)	(0.9,0.2,0.9)
4	(0.7,0.2,0.9)	(0.5,0.3,0.8)	(0.8,0.2,0.7)
5	(0.8,0.2,0.7)	(0.9,0.3,0.9)	(0.9,0.2,0.9)
6	(0.9,0.3,0.7)	(0.8,0.2,0.9)	(0.9,0.2,0.3)
7	(0.9,0.2,0.3)	(0.9,0.2,0.9)	(0.5,0.3,0.8)
8	(0.7,0.4,0.8)	(0.9,0.2,0.9)	(0.5,0.2,0.9)

Table 6. Tabular representation of RPN in Disagree - NISES

Failure Mode	Severity	Occurrence	Detection
1	(0.1,0.7,0.5)	(0.4,0.4,0.3)	(0.3,0.6,0.1)
2	(0.1,0.7,0.3)	(0.3,0.7,0.1)	(0.4,0.6,0.1)
3	(0.1,0.6,0.5)	(0.1,0.8,0.4)	(0.1,0.7,0.3)
4	(0.2,0.9,0.3)	(0.3,0.6,0.4)	(0.4,0.6,0.3)
5	(0.3,0.9,0.1)	(0.4,0.3,0.5)	(0.2,0.9,0.2)
6	(0.2,0.6,0.1)	(0.4,0.8,0.1)	(0.2,0.9,0.3)
7	(0.1,0.8,0.3)	(0.2,0.9,0.3)	(0.1,0.8,0.1)
8	(0.1,0.7,0.2)	(0.1,0.8,0.2)	(0.1,0.7,0.1)

Remark 5.2. Now we can find the NISES by using the following way,
(max of degree of membership $\{\beth_1, \beth_2, \beth_3, \beth_4\}$, min of degree of indeterminacy $\{\beth_1, \beth_2, \beth_3, \beth_4\}$, min of degree of non- membership $\{\beth_1, \beth_2, \beth_3, \beth_4\}$).

TABLE 7. Tabular representation of RPN in NISES

Failure Mode	Severity	Occurrence	Detection
1	(0.1,0.3,0.5)	(0.4,0.1,0.3)	(0.3,0.2,0.1)
2	(0.1,0.1,0.3)	(0.3,0.1,0.1)	(0.4,0.1,0.1)
3	(0.1,0.2,0.5)	(0.1,0.2,0.4)	(0.1,0.2,0.3)
4	(0.2,0.2,0.3)	(0.3,0.3,0.4)	(0.4,0.2,0.3)
5	(0.3,0.2,0.1)	(0.4,0.3,0.5)	(0.2,0.2,0.2)
6	(0.2,0.3,0.1)	(0.4,0.2,0.1)	(0.2,0.2,0.3)
7	(0.1,0.2,0.3)	(0.2,0.2,0.3)	(0.1,0.3,0.1)
8	(0.1,0.4,0.2)	(0.1,0.2,0.2)	(0.1,0.2,0.1)

Remark 5.3. $\underline{lim(NISES)}$ or $\underline{lim} = \dfrac{\text{degree of membership + degree of indeterminacy}}{2}$

$\overline{lim(NISES)}$ or $\overline{lim} = \dfrac{\text{degree of indeterminacy + degree of non-membership}}{2}$.

TABLE 8. NISES failure modes assessment matrix

Failure Mode	Severity	Occurrence	Detection
1	[0.2,0.4]	[0.25,0.2]	[0.25,0.15]
2	[0.1,0.2]	[0.2,0.1]	[0.25,0.1]
3	[0.15,0.35]	[0.15,0.3]	[0.15,0.25]
4	[0.2,0.25]	[0.3,0.35]	[0.3,0.25]
5	[0.25,0.15]	[0.35,0.4]	[0.2,0.2]
6	[0.25,0.2]	[0.3,0.15]	[0.2,0.25]
7	[0.15,0.25]	[0.2,0.25]	[0.2,0.2]
8	[0.25,0.3]	[0.15,0.2]	[0.15,0.15]

Calculate the decision matrix for failure mode, using the formula $|\underline{lim(NISES)} - \overline{lim(NISES)}|$.

$$\widetilde{DM} = \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \end{matrix} \begin{bmatrix} 0.2 & 0.05 & 0.1 \\ 0.1 & 0.1 & 0.15 \\ 0.2 & 0.15 & 0.1 \\ 0.05 & 0.05 & 0.05 \\ 0.1 & 0.05 & 0 \\ 0.05 & 0.15 & 0.05 \\ 0.1 & 0.05 & 0 \\ 0.05 & 0.05 & 0 \end{bmatrix}$$

Step 3. Find AV of all attributes as follows.

$$AV_1 = \frac{0.05 + 0.1 + 0.2 + 0.05 + 0.1 + 0.2 + 0.1 + 0.05}{8} = 0.09$$

$$AV_2 = \frac{0.15 + 0.1 + 0.15 + 0.05 + 0.05 + 0.05 + 0.05 + 0.05}{8} = 0.08$$

$$AV_3 = \frac{0.05 + 0.15 + 0.1 + 0.05 + 0 + 0.1 + 0 + 0}{8} = 0.05$$

Step 4. The values of PDA solution for first attribute 'S' are given below

$$PDA_{11} = \frac{max(0, (0.09 - 0.2))}{0.09} = 0$$

$$PDA_{21} = \frac{max(0, (0.09 - 0.1))}{0.09} = 0$$

$$PDA_{31} = \frac{max(0, (0.09 - 0.2))}{0.09} = 0$$

$$PDA_{41} = \frac{max(0, (0.09 - 0.05))}{0.09} = 0.444$$

$$PDA_{51} = \frac{max(0, (0.09 - 0.1))}{0.09} = 0$$

$$PDA_{61} = \frac{max(0, (0.09 - 0.05))}{0.09} = 0.444$$

$$PDA_{71} = \frac{max(0, (0.09 - 0.1))}{0.09} = 0$$

$$PDA_{81} = \frac{max(0, (0.09 - 0.05))}{0.09} = 0.444$$

Other values of the PDA solution is provided in Table 9 .

Table 9. Values of PDA solution

FM	S	O	D
1	0	0.375	0
2	0	0	0
3	0	0	0
4	0.444	0.375	0
5	0	0.375	0
6	0.444	0	0
7	0	0.375	0
8	0.444	0.375	0

.

'S'- NDA solution is given below.

$$NDA_{21} = \frac{max(0, (0.2 - 0.09))}{0.09} = 1.222$$

$$NDA_{22} = \frac{max(0,(0.1-0.09))}{0.09} = 0.111$$

$$NDA_{23} = \frac{max(0,(0.2-0.09))}{0.09} = 1.222$$

$$NDA_{24} = \frac{max(0,(0.05-0.09))}{0.09} = 0$$

$$NDA_{25} = \frac{max(0,(0.1-0.09))}{0.09} = 0.111$$

$$NDA_{26} = \frac{max(0,(0.05-0.09))}{0.09} = 0$$

$$NDA_{27} = \frac{max(0,(0.1-0.09))}{0.09} = 0.111$$

$$NDA_{28} = \frac{max(0,(0.05-0.09))}{0.09} =0$$

Table10 indicates the other values of the NDA solution namely 'O' and 'D'.

Table 10. Values of NDA solution

FM	S	O	D
1	1.222	0	1
2	0.111	0.250	2
3	1.222	0.875	1
4	0	0	0
5	0.111	0	0
6	0	0.875	0
7	0.111	0	0
8	0	0	0

Step 5. Determine WSPDA and WSNDA for all alternatives, using attribute weights. By assigning equal weights to all the criteria we have the following table.

Table 11. Weight attributes

Attribute	S	O	D
ω_j	1/3	1/3	1/3

TABLE 12. Values of the weighted positive distances

FM	S	O	D	Sum
1	0	0.124	0	0.124
2	0	0	0	0
3	0	0	0	0
4	0.147	0.124	0	0.271
5	0	0.124	0	0.124
6	0.147	0	0	0.147
7	0	0.124	0	0.124
8	0.147	0.124	0	0.271

.

TABLE 13. Values of the weighted negative distances

FM	S	O	D	Sum
1	0.403	0	0.33	0.733
2	0.037	0.083	0.66	0.779
3	0.403	0.289	0.33	1.022
4	0	0	0	0
5	0.037	0	0	0.037
6	0	0.289	0	0.289
7	0.037	0	0	0.037
8	0	0	0	0

.

Step 6. Determine the weighted normalized PDA of each failure mode from Equation (9)

$$WNPDA_1 = \frac{0.124}{0.271} = 0.458$$

$$WNPDA_2 = \frac{0}{0.271} = 0$$

$$WNPDA_3 = \frac{0}{0.271} = 0$$

$$WNPDA_4 = \frac{0.271}{0.271} = 1$$

$$WNPDA_5 = \frac{0.124}{0.271} = 0.458$$

$$WNPDA_6 = \frac{0.147}{0.271} = 0.542$$

$$WNPDA_7 = \frac{0.124}{0.271} = 0.458$$

$$WNPDA_8 = \frac{0.271}{0.271} = 1$$

Next we determine the weighted normalized NDA of each failure mode from Equation (10)

$$WNNDA_1 = \frac{0.733}{1.022} = 0.717$$

$$WNNDA_2 = \frac{0.779}{1.022} = 0.782$$

$$WNNDA_3 = \frac{1.022}{1.022} = 1$$

$$WNNDA_4 = \frac{0}{1.022} = 0$$

$$WNNDA_5 = \frac{0.037}{1.022} = 0.036$$

$$WNNDA_6 = \frac{0.289}{1.022} = 0.283$$

$$WNNDA_7 = \frac{0.037}{1.022} = 0.036$$

$$WNNDA_8 = \frac{0}{1.022} = 0$$

Step 7. Determine the assessment score using the Equation (11)

$$AS_1 = \frac{1}{2}(0.458 + 0.717) = 0.588$$

$$AS_2 = \frac{1}{2}(0 + 0.782) = 0.391$$

$$AS_3 = \frac{1}{2}(0 + 1) = 0.5$$

$$AS_4 = \frac{1}{2}(1 + 0) = 0.5$$

$$AS_5 = \frac{1}{2}(0.458 + 0.036) = 0.247$$

$$AS_6 = \frac{1}{2}(0.542 + 0.283) = 0.413$$

$$AS_7 = \frac{1}{2}(0.458 + 0.036) = 0.247$$

$$AS_8 = \frac{1}{2}(1 + 0) = 0.5$$

Step 8. Ranking the failure mode

$$AS_1 \succ AS_3 \approx AS_4 \approx AS_8 \approx AS_6 \succ AS_2 \succ AS_5 \approx AS_7.$$

5.2. *Comparison of Song et al. [20] approach and our approach*

A comparison of Song et al. [20] approach and our approach is provided in Table 14 below.

Table 14. Comparison of the two approaches

Ranking	Alternative (s)	Best Alternative
Existing	$1 \succ 7 \succ 5 \succ 6 \succ 8 \succ 4 \succ 3 \succ 2$	1
Our approach	$1 \succ 3 \approx 4 \approx 8 \approx 6 \succ 2 \succ 5 \approx 7$	1

Both, our approach and the method proposed by Song et al. [20] yield equivalent results. However, when juxtaposed with Song et al.'s method, our approach boasts a streamlined process and straightforward calculations that are more intuitive and easier to comprehend. This comparative analysis is also visually represented through a graph, as illustrated below.

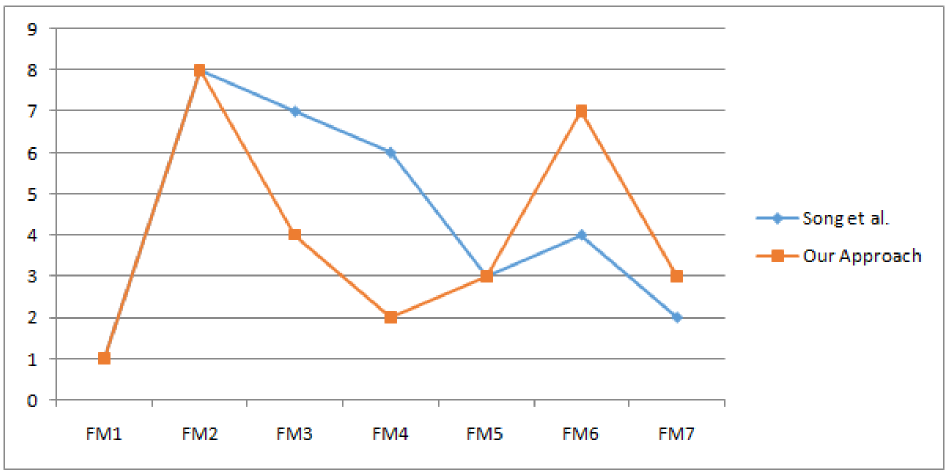

Figure 2. Comparative analysis of our approach with [20]

In the subsequent section, we delve into another application of the Neutrosophic Inverse Soft Expert Set, namely the Additive Ratio Assessment Simplified Version method. What sets this approach apart is its novel computation of optimal score values, which relies on the lower and upper limits of neutrosophic inverse soft expert sets. This innovation represents a significant advancement compared to the methodology employed in the Additive Ratio Assessment method by Zavadskas et al. [24]

We proceed by presenting an algorithm for the Additive Ratio Assessment Simplified Version method utilizing neutrosopic inverse soft expert sets. The algorithm consists of eight key steps. Central to this process is the construction of an $m \times n$ decision matrix (r_{ij}) where m signifies the cardinality of the universal set $|U|$, and n represents the cardinality of set $|\gimel|$. This decision matrix is then evaluated based on input from the decision makers. Subsequently, a Weighted Normalized Decision Matrix (WNDM) is derived, and an optimal score value is computed using the optimality function (OF). Following this, the Utility Degree (UD) is calculated, and the conclusion is determined based on the value of the utility degree.

6. Additive Ratio Assessment-Simplified Version Method in neutrosophic inverse soft expert set

Zavadskas et al. [24] pioneered the concept of the Additive Ratio Assessment (ARAS) method. The novelty of this method lies in its ability to facilitate the selection of the optimal alternative, taking into account the number of attributes. The final ranking of alternatives is accomplished by assessing the utility degree of each alternative. In the following section, we introduce the algorithm for the Additive Ratio Assessment - Simplified Version (ARAS-SV) method as outlined below.

6.1. *Algorithm on additive ratio assessment-simplified version Method using neutrosophic inverse soft expert set*

Step 1. Construct the decision matrix based on the information received from the decision maker using NISES and remark (5.3), namely $X = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ \vdots & \vdots & \dots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix}$ (or) $X = (r_{ij})_{m\times n}$.

Step 2. Normalized Decision Matrix (NDM_{ij}) is defined as follows.

$$NDM_{ij} = \frac{r_{ij}}{\sum\limits_{i=1}^{m} r_{ij}}; j = 1, 2..., n \tag{12}$$

Step 3. Choose the weight of attributes w_j from the decision maker.

Step 4. Form the weighted normalized decision matrix (WNDM) as follows.

$$WNDM_{ij} = r^*_{ij} \cdot w_j; i = 1, 2, ..., m, j = 1, 2..., n \tag{13}$$

Step 5. Construct the optimality function (OF) as follows.

$$OF_i = \sum_{j=1}^{n} WNDM; i = 1, 2, ..., m \tag{14}$$

Step 6. Calculate optimality score value using optimality function defined in remark (5.3) as follows.

$$S_i = \frac{\underline{\underline{lim}} + \overline{\overline{lim}}}{2} \tag{15}$$

Step 7. Calculate the utility degree (UD) using this formula

$$UD_i = \frac{S_i}{V_0}, i = 1, 2, ..., m, \tag{16}$$

where V_0 is the maximum value of S_i.

Step 8. UD_i values are arranged in descending order in order to find the final ranking.

6.2. *Illustrative Example*

Problem statement

Imagine a scenario where a patient needs to make a crucial decision about selecting the most suitable doctor among four experts, each specializing in different fields of medical treatment. The challenge at hand is to make an informed choice based on various parameters. We denote the four doctors as $U = \{\vartheta_1, \vartheta_2, \vartheta_3, \vartheta_4\}$ and define a set of parameters $\Upsilon = \{\daleth_1, \daleth_2, \daleth_3, \daleth_4, \daleth_5, \daleth_6\}$. These parameters encompass factors such as hospital expenditure ($\daleth_1$), the efficiency of diagnosis by doctors ($\daleth_2$), doctor availability ($\daleth_3$), hospital provisions ($\daleth_4$), doctors' experience in treating the specific disease ($\daleth_5$), and the distance of the hospital from the patient's residence ($\daleth_6$). To navigate this decision-making process systematically, we employ the ARAS-SV method, breaking it down step by step as follows.

The problem is to choose a best doctor by a patient based on the parameters, listed.

Let us apply ARAS-SV method in the above situation step by step below.

Construct NISES as follows.

TABLE 15. Neutrosophic inverse soft expert sets

N_S^U	ϑ_1	ϑ_2	ϑ_3	ϑ_4
$(\daleth_1, \varrho_1, 1)$	(0.2,0.4,0.9)	(0.3,0.8,0.1)	(0.3,0.6,0.1)	(0.2,0.4,0.7)
$(\daleth_1, \varrho_1, 0)$	(0.5,0.1,0.7)	(0.5,0.3,0.1)	(0.4,0.5,0.1)	(0.1,0.4,0.2)
$(\daleth_1, \varrho_2, 1)$	(0.9,0.7,0.3)	(0.8,0.5,0.6)	(0.9,0.2,0.5)	(0.7,0.4,0.9)
$(\daleth_1, \varrho_2, 0)$	(0.4,0.8,0.1)	(0.4,0.2,0.8)	(0.1,0.9,0.2)	(1,0.8,0.3)
$(\daleth_2, \varrho_1, 1)$	(0.1,0.2,0.3)	(0.9,0.8,0.6)	(0.4,0.2,0.2)	(0.4,0.8,0.1)
$(\daleth_2, \varrho_1, 0)$	(0.8,0.2,0.4)	(0.3,0.5,0.7)	(0.6,0.3,0.7)	(0.7,0.6,0.3)
$(\daleth_2, \varrho_2, 1)$	(0.9,0.4,0.2)	(0.5,0.3,0.2)	(0.3,0.6,0.7)	(0.5,0.5,0.5)
$(\daleth_2, \varrho_2, 0)$	(0.4,0.7,0.3)	(0.8,0.2,0.4)	(0,0.3,0.8)	(0.3,0.8,0)
$(\daleth_3, \varrho_1, 1)$	(0.3,0.4,05)	(0.4,0.2,0.6)	(0.1,0.7,0.9)	(0.4,0.1,0.3)
$(\daleth_3, \varrho_1, 0)$	(0.8,0.7,03)	(0.6,0.2,0.5)	(0.3,0.7,0.1)	(0.5,0.9,0.2)
$(\daleth_3, \varrho_2, 1)$	(0.6,0.3,0.8)	(0.4,0.5,0.6)	(0.6,0.2,0.9)	(0.8,0.5,0.3)
$(\daleth_3, \varrho_2, 0)$	(0.6,0.9,0.1)	(0.9,0.4,0.5)	(0.2,1,0.8)	(0.6,0.4,0.1)

.

TABLE 16. Tabular representation of Agree - NISES

N_S^U	$(\daleth_1, \varrho_1, 1)$	$(\daleth_1, \varrho_2, 1)$	$(\daleth_2, \varrho_1, 1)$	$(\daleth_2, \varrho_2, 1)$	$(\daleth_3, \varrho_1, 1)$	$(\daleth_3, \varrho_2, 1)$
ϑ_1	(0.2,0.4,0.9)	(0.9,0.7,0.3)	(0.1,0.2,0.3)	(0.9,0.4,0.2)	(0.3,0.4,0.5)	(0.6,0.3,0.8)
ϑ_2	(0.3,0.8,0.1)	(0.8,0.5,0.6)	(0.9,0.8,0.6)	(0.5,0.3,0.2)	(0.4,0.2,0.6)	(0.4,0.5,0.6)
ϑ_3	(0.3,0.6,0.1)	(0.9,0.2,0.5)	(0.4,0.2,0.2)	(0.3,0.6,0.7)	(0.1,0.7,0.9)	(0.6,0.2,0.9)
ϑ_4	(0.2,0.4,0.7)	(0.7,0.4,0.9)	(0.4,0.8,0.1)	(0.5,0.5,0.5)	(0.4,0.1,0.3)	(0.8,0.5,0.3)

.

Table 17. Tabular representation of Disagree - NISES

N_S^U	$(\gimel_1, \varrho_1, 0)$	$(\gimel_1, \varrho_2, 0)$	$(\gimel_2, \varrho_1, 0)$	$(\gimel_2, \varrho_2, 0)$	$(\gimel_3, \varrho_1, 0)$	$(\gimel_3, \varrho_2, 0)$
ϑ_1	(0.5,0.1,0.7)	(0.4,0.8,0.1)	(0.8,0.2,0.4)	(0.4,0.7,0.3)	(0.8,0.7,0.3)	(0.6,0.9,0.1)
ϑ_2	(0.5,0.3,0.1)	(0.4,0.2,0.8)	(0.3,0.5,0.7)	(0.8,0.2,0.4)	(0.6,0.2,0.5)	(0.9,0.4,0.5)
ϑ_3	(0.4,0.5,0.1)	(0.1,0.9,0.2)	(0.6,0.3,0.7)	(0,0.3,0.8)	(0.3,0.7,0.1)	(0.2,1,0.8)
ϑ_4	(0.1,0.4,0.2)	(1,0.8,0.3)	(0.7,0.6,0.3)	(0.3,0.8,0)	(0.5,0.9,0.2)	(0.6,0.4,0.1)

Following the procedure adopted in Remark 5.2, we calculate NISES as follows,

Table 18. Tabular representation of NISES

N_S^U	$\gimel_1$	$\gimel_2$	$\gimel_3$	$\gimel_4$	$\gimel_5$	$\gimel_6$
ϑ_1	(0.2,0.1,0.7)	(0.4,0.7,0.1)	(0.1,0.2,0.3)	(0.4,0.4,0.1)	(0.3,0.4,0.3)	(0.6,0.3,0.1)
ϑ_2	(0.3,0.3,0.1)	(0.4,0.2,0.6)	(0.3,0.5,0.6)	(0.5,0.2,0.2)	(0.4,0.2,0.5)	(0.4,0.4,0.5)
ϑ_3	(0.3,0.5,0.1)	(0.1,0.2,0.2)	(0.4,0.2,0.2)	(0,0.3,0.7)	(0.1,0.7,0.1)	(0.2,0.2,0.8)
ϑ_4	(0.1,0.4,0.2)	(0.1,0.4,0.3)	(0.4,0.6,0.1)	(0.3,0.5,0)	(0.4,0.1,0.2)	(0.6,0.4,0.1)

Step 1. Define the decision matrix X using the decision makers information as namely from Table 18 and remark (5.3) as follows.

$$X = \begin{array}{c} \\ \vartheta_1 \\ \vartheta_2 \\ \vartheta_3 \\ \vartheta_4 \end{array} \begin{array}{c} \begin{array}{cccccc} \gimel_1 & \gimel_2 & \gimel_3 & \gimel_4 & \gimel_5 & \gimel_6 \end{array} \\ \begin{pmatrix} (.15, .4) & (.65, .4) & (.15, .25) & (.4, .25) & (.35, .35) & (.45, .2) \\ (.4, .2) & (.3, .4) & (.4, .55) & (.35, .2) & (.3, .35) & (.4, .45) \\ (.4, .3) & (.15, .2) & (.3, .2) & (.15, .5) & (.4, .4) & (.2, .5) \\ (.25, .3) & (.25, .35) & (.5, .35) & (.4, .25) & (.25, .15) & (.5, .25) \end{pmatrix} \end{array}$$

Step 2. Calculate the NDM using the equation (12).

$$\begin{array}{c} \\ \vartheta_1 \\ \vartheta_2 \\ \vartheta_3 \\ \vartheta_4 \end{array} \begin{array}{c} \begin{array}{cccccc} \gimel_1 & \gimel_2 & \gimel_3 & \gimel_4 & \gimel_5 & \gimel_6 \end{array} \\ \begin{pmatrix} (.125, .333) & (.481, .296) & (.111, .185) & (.308, .208) & (.269, .280) & (.290, .143) \\ (.333, .166) & (.222, .296) & (.296, .407) & (.269, .166) & (.231, .280) & (.258, .321) \\ (.333, .250) & (.111, .146) & (.222, .148) & (.115, .417) & (.308, .320) & (.129, .357) \\ (.208, .250) & (.185, .259) & (.370, .259) & (.308, .208) & (.192, .120) & (.321, .179) \end{pmatrix} \end{array}$$

Step 3. Form the weight of attributes w_j from the decision maker namely patient as follows.

$\gimel_1$ = cost of hospital expenditure = 0.1

$\gimel_2$ = diagnosing efficiency of doctors = 0.2

$\gimel_3$ = availability of doctors = 0.2

$\gimel_4$ = hospital provisions = 0.2

$\gimel_5$ = doctors experience in curing the disease = 0.2

$\gimel_6$ = the hospital distance from the patient house = 0.1

Attribute	$\gimel_1$	$\gimel_2$	$\gimel_3$	$\gimel_4$	$\gimel_5$	$\gimel_6$
w_j	0.1	0.2	0.2	0.2	0.2	0.1

Step 4. Construct the weighted normalized decision matrix using the equation (13)

$$\begin{array}{c} \\ \vartheta_1 \\ \vartheta_2 \\ \vartheta_3 \\ \vartheta_4 \end{array} \begin{array}{c} \begin{array}{cccccc} \gimel_1 & \gimel_2 & \gimel_3 & \gimel_4 & \gimel_5 & \gimel_6 \end{array} \\ \begin{pmatrix} (.013, .033) & (.096, .059) & (.022, .037) & (.062, .042) & (.054, .029) & (.029, .014) \\ (.033, .025) & (.022, .029) & (.044, .030) & (.023, .083) & (.026, .071) & (.013, .036) \\ (.033, .017) & (.044, .059) & (.059, .081) & (.054, .033) & (.052, .064) & (.026, .032) \\ (.021, .025) & (.037, .052) & (.074, .052) & (.062, .044) & (.064, .036) & (.032, .018) \end{pmatrix} \end{array}$$

Step 5. Calculate the optimality function using the equation (14)

$OF_1 = (0.013, 0.033)+(0.096, 0.059)+(0.022, 0.037)+(0.062, 0.042)+(0.054, 0.029)+(0.029, 0.014) = (0.276, 0.214)$.

$OF_2 = (0.033, 0.025)+(0.022, 0.029)+(0.044, 0.030)+(0.023, 0.083)+(0.026, 0.071)+(0.013, 0.036) = (0.161, 0.274)$.

$OF_3 = (0.033, 0.017)+(0.044, 0.059)+(0.059, 0.081)+(0.054, 0.033)+(0.052, 0.064)+(0.026, 0.032) = (0.268, 0.286)$.

$OF_4 = (0.021, 0.025)+(0.037, 0.052)+(0.074, 0.052)+(0.062, 0.044)+(0.064, 0.036)+(0.032, 0.018) = (0.290, 0.227)$.

Step 6. Construct optimal score value using optimality function as follows.

$$S_i = \frac{\underline{\underline{lim}} + \overline{lim}}{2}$$

$$S_1 = \frac{0.276 + 0.214}{2} = 0.245$$

$$S_2 = \frac{0.161 + 0.274}{2} = 0.218$$

$$S_3 = \frac{0.268 + 0.286}{2} = 0.277$$

$$S_4 = \frac{0.290 + 0.227}{2} = 0.209$$

Step 7. Construct the utility degree using the equation (16)

$$UD_1 = \frac{0.245}{0.277} = 0.884$$

$$UD_2 = \frac{0.218}{0.277} = 0.787$$

$$UD_3 = \frac{0.277}{0.277} = 1$$

$$UD_4 = \frac{0.209}{0.277} = 0.755$$

Step 8. The final ranking of alternatives and conclusion.
Finally, the third doctor ϑ_3 is the best choice to patient for treatment as per the final ranking.
$\vartheta_3 > \vartheta_1 > \vartheta_2 > \vartheta_4$.

7. Result and discussion

The integration of the Neutrosophic Inverse Soft Expert Sets technique into our Failure Mode and Effect Analysis approach has yielded a host of insightful outcomes. Through a meticulous comparative analysis with the methodology proposed by Song et al., several distinct advantages of our approach have come to light.

One prominent finding is the enhanced efficiency in the assessment of Risk Priority Numbers. By harnessing the power of NISES, we have devised a streamlined and transparent system for allocating weights to Severity (S), Occurrence (O), and Detection (D). This enhancement not only expedites the computation process but also enables a more intuitive evaluation of risk factors. In practical terms, this translates to swifter and more precise decision-making, a crucial attribute in industries where rapid response to potential failures is imperative.

Furthermore, our approach showcases commendable resilience in scenarios characterized by uncertainties and imprecise information. The inherent adaptability of neutrosophic sets allows us to effectively navigate the complexities of real-world situations. This adaptability proves invaluable in industries subject to dynamic and swiftly changing environments, providing a robust framework for risk assessment. Additionally, the NISES technique exhibits noteworthy versatility in accommodating a wide spectrum of expert judgments and assessments. Its adaptability to varying levels of expertise within a team ensures that insights from experts of different domains can be seamlessly integrated into the analysis. This inclusive approach not only fortifies the reliability of the results but also fosters a collaborative decision-making environment, a critical aspect in complex industrial settings.

In conclusion, the integration of NISES into FMEA constitutes a significant leap forward in the realm of risk assessment methodologies. Its impact is evidenced not only in the streamlined computation process but also in its adeptness at handling uncertainties and its inclusivity in expert assessments.

As industries continue to evolve, the NISES technique is poised to be a formidable and indispensable tool in navigating the intricate landscape of risk assessment and decision-making.

Our results exhibit superiority through a streamlined computation process facilitated by the integration of Neutrosophic Inverse Soft Expert Sets. This simplification not only accelerates the assessment of Risk Priority Numbers but also enhances the transparency and intuitiveness of the evaluation process. The assignment of weights to Severity (S), Occurrence (O), and Detection (D) factors is executed with greater efficacy, eliminating potential complexities and uncertainties in the weighting process. This, in turn, leads to a more accurate and reliable risk assessment. The adaptability of our approach to uncertainties and imprecise information, owing to the NISES technique, ensures its effectiveness in dynamic and rapidly changing environments. Additionally, our approach excels in inclusivity, accommodating a diverse range of expert judgments and assessments. This feature enables insights from experts with varying levels of expertise to be seamlessly integrated into the analysis, resulting in a more comprehensive and reliable evaluation. Ultimately, our approach yields equivalent optimal alternatives while offering potential for rapid decision-making, positioning it as a valuable tool in industries where timely and precise decision-making is critical.

8. **Limitations**

While the Neutrosophic Inverse Soft Expert Sets technique presents promising advancements in Failure Mode and Effect Analysis, it is essential to acknowledge its limitations.

1. Dependence on Expert Judgments: Like any expert-based approach, the effectiveness of NISES relies heavily on the quality and reliability of expert assessments. Inaccurate or biased judgments can introduce errors into the analysis, potentially leading to suboptimal decisions.

2. Sensitivity to Parameter Selection: The choice of parameters, such as the thresholds for Risk Priority Numbers or the weighting factors, can significantly influence the results. Selecting inappropriate values may lead to skewed assessments and potentially incorrect prioritization of failure modes.

3. Complexity of Implementation: Implementing the NISES technique may require a certain level of familiarity with neutrosophic theory and soft computing concepts. This complexity could pose a challenge for practitioners without a strong background in these areas.

4. Limited Historical Data: In situations where there is a scarcity of historical data or prior instances of similar failure modes, the accuracy and reliability of the NISES technique may be compromised. This is especially pertinent in novel or highly specialized industries.

5. Difficulty in Quantifying Soft Expert Opinions: Soft expert opinions, inherent to the NISES technique, can be challenging to quantify objectively. This subjectivity introduces an additional layer of uncertainty, potentially impacting the precision of the results.

6. Computational Overhead:Depending on the scale and complexity of the FMEA, the computational requirements for implementing NISES may be higher compared to more conventional approaches. This could lead to longer processing times, particularly for large-scale analyses.

7. Lack of Standardization: As a relatively new methodology, NISES may not yet have established standardized procedures or widely-accepted best practices. This can lead to variability in its application across different industries and contexts.

8. Potential for Overfitting: In situations where the NISES technique is applied to a limited dataset, there is a risk of overfitting, where the model may perform exceptionally well on the available data but struggle to generalize to new, unseen scenarios.

It's important to recognize these limitations and consider them in the context of specific applications. Addressing these challenges through ongoing research and refinement of the methodology will be crucial in realizing the full potential of NISES in FMEA.

9. **Conclusion and Future Work**

In conclusion, the integration of the NISES technique into FMEA approach presents a significant advancement in risk assessment methodologies. The simplified computation of RPN weights enhances the practicality and accessibility of the method, making it a valuable tool for industries facing complex decision-making scenarios.

Looking ahead, our research aims to explore the potential extensions of this approach into the realms of soft-rough fuzzy set and soft fuzzy rough set methodologies within the context of FMEA. This expansion holds promise for further refinement and enhancement of risk assessment techniques, catering to a broader spectrum of industries and applications.

Additionally, we plan to delve deeper into the application of neutrosophic sets within our approach. This presents an exciting avenue for research, with the potential to revolutionize risk analysis methodologies by incorporating a broader spectrum of uncertainties and complexities. By leveraging the power of neutrosophic sets, we anticipate even greater strides in the field of risk assessment and decision-making.

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References

1. Abdel-Basset, M., Chakrabortty, R.K., and Gamal, A. (2023). Multi-Criteria Decision Making Theory and Applications in Sustainable Healthcare *(1st ed.). CRC Press.*
2. Ahmed M.AbdelMouty, Ahmed Abdel-Monem. (2023) Neutrosophic MCDM Methodology for Assessment Risks of Cyber Security in Power Management, *Neutrosophic Systems with Applications*, 3, 5361
3. M. Akram, A. Luqman and J. C. R. Alcantud. (2012) Risk evaluation in failure modes and effects analysis:hybrid TOPSIS and ELECTRE I solutions with Pythagorean fuzzy information. *Neural Computing and Applications*, 32(2).
4. S. Alkhazaleh and A. R. Salleh. (2011) Soft expert sets, *Advances in Decision Sciences*, 2011, Article ID. 757868.
5. K. S. Chin, Y. M. Wang, G. K. Poon and J. B. Yang. (2009) Failure mode and effects analysis by data envelopment analysis, *Decision Support System*, 48(1), 246-256.
6. C. L. Chang, C. C. Wei and V. Lee. (1999) Failure mode and effects analysis using fuzzy method and grey theory, *Kybernetes*, 28(9), 1072-1080.
7. F. Feng, X. Liu, Violeta Leoreanu-Fotea and Y. B. Jun. (2011) Soft sets and soft rough sets, *Information Sciences*, 181, 1125-1137.
8. Gilchrist, W. (1993). Modeling Failure Modes and Effects Analysis, *International Journal of Quality and Reliability Management* 10(5),16-23.
9. M. Keshavarz Ghorabaee, E. K. Zavadskas, L. Olfat and Z. Turskis. (2015) Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS), *Informatica* 26, 435-451.
10. A. M. Khalil and N. Hassan. (2019) Inverse fuzzy soft set and its application in decision making, *International Journal of Information and Decision Sciences*, 11(1), 73-92.
11. Hamiden Abd El- Wahed Khalifa, Pavan Kumar and Seyedali Mirjalili. (2021). A KKM approach for inverse capacitated transportation problem in neutrosophic environment. *Sadhana.*, 46(166), 1-8.
12. Hamiden Abd El- Wahed Khalifa, Pavan Kumar and Florentin Smarandache. (2020). On Optimizing Neutrosophic Complex Programming Using Lexicographic Order. *Neutrosophic Sets and Systems*, 32, 330- 343.
13. Hamiden Abd El- Wahed Khalifa, Pavan Kumar(2020). A Novel Method for Neutrosophic Assignment Problem by using Interval-Valued Trapezoidal Neutrosophic Number. *Neutrosophic Sets and Systems*, 36, 24-36.
14. Hamiden Abd El-Wahed Khalifa , Majed G. Alharbi and Pavan Kumar (2021). On Determining the Critical Path of Activity Network with Normalized Heptagonal Fuzzy Data. *Hindawi,Wireless Communications and Mobile Computing*, 2021, Article ID 6699403.
15. H. C. Liu, L. Liu and Q. H. Bian. (2010) Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory, *Expert Systems with Applications*, 38(4), 4403-4415.
16. Mona Mohamed, Karam M. Sallam. (2023) Leveraging Neutrosophic Uncertainty Theory toward Choosing Biodegradable Dynamic Plastic Product in Various Arenas, *Neutrosophic Systems With Applications*, 5, 19.
17. D. Molodtsov. (1999) Soft Set Theory First Results, *Computers and Mathematics with Applications*, 37, 19-31.
18. A. Pillay and J. Wang. (2003) Modified failure mode and effects analysis using approximate reasoning, *Reliability Engineering and System Safety*, 79, 69-85.
19. F. Smarandache. (1998) Neutrosophy: Neutrosophic Probability Set and Logic: Analytic Synthesis & Synthetic Analysis, *American Research Press., Rehoboth, MA, USA*.

20. W. Song, X. Ming, Z. Wu and B. Zhu. (2013) A rough TOPSIS Approach for Failure Mode and Effects Analysis in Uncertain Environmrnts, *Quality and Reliability Engineering International*, wileyonlinelibrary.com.
21. N. Sathiyaseelan, S. Vijayabalaji and J. C. R. Alcantud. (2023) Symmetric Matrices on Inverse Soft Expert Sets and Their Applications, *Symmetry*, 15(2), article no. 313.
22. K. Xu, L. C. Tang, M. Xie, S. L. Ho, and M. L. Zhu. (2002) Fuzzy assessment of FMEA for engine systems, *Reliability Engineering and System Safety*, 75(1), 17-29.
23. L. A. Zadeh. (1965) Fuzzy sets, *Inf. Control.*, 8(3), 338-353.
24. E. K. Zavadskas and Z. Turskis. (2010) A new additive ratio assessment (ARAS) method in multi criteria decision-making, *Technological and Economic Development of Economy.*, 16(2), 159-172.

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