Strategic Decision-Making Enhancement Framework (SDE-Framework): Leveraging Neutrosophic Logic and Fuzzy Mathematics for Optimized Outcomes in IT Management and Computational Systems

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Abstract

The created SDE-Framework combines neutronosophic logic and fuzzy mathematics in a novel method, aiming at facilitating more informed decision outcomes in computational systems and information technology management. This method hopes to aid in determining strategic solutions by controlling the expected sophistication and ambiguity in these two technologically dynamic industries. Neutronosophic logic divides data into three components: truth, indeterminacy, and falsity, build an exhaustive technique for addressing contradiction and indeterminacy. This significantly increases the method by enabling a more complete exploration of potential options with ambiguous and inadequate data. Second, the fuzzy mathematics gives a valuable contribution. It offers a refined method for managing the levels of probability and certainty through membership features, resulting in more exact and flexible evaluations. By the usage of such compared sophisticated mathematics concepts, SDE-Framework addresses potential decision-making scenarios by letting the computer formulates do the judgements for the determinable and in determinable explicit data. The subsequent crucial parameters are adopted to tolerance values: validity and responsibility, falseness foreach, indeterminacy magnitude to each, and truth value. This guarantees its combination of complexity supportive rand reading of actual surroundings.

Keywords: Adaptive Systems; Decision-Making; Fuzzy Mathematics; Management; Neutrosophic Logic; Uncertainty Handling

1. Introduction

In the rapidly advancing field of computational decision-making, there is a pressing need for frameworks that can effectively navigate the complexities and inherent ambiguities of data-intensive

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environments. Traditional decision-making tools often struggle with incomplete or contradictory information, which can lead to suboptimal outcomes in scenarios where strategic decisions are critical. The SDE-Framework, which introduces the incorporation of neutrosophic logic and fuzzy mathematics, is a pioneering approach to address the abovementioned issue at the time. Neutrosophic logic differs from traditional binary logic by adding a third value of indeterminacy in addition to truth and falsity. With that, traditional binary systems may struggle to process uncertainty and conflicting data, which in real life rarely comes in perfect black or white. Similarly, fuzzy mathematics introduces tools for working with conventional truth values in terms of "degree of trueness" rather than absolute attributes. It allows for more cautious, sensitive, uncertain, or convicted declarations while simultaneously giving room for error. Combining the two theories into the SDE-Framework allows the system to adequately interpret and evaluate information that other frameworks may misinterpret or oversimplify in binary states. The framework could be applicable in IT management, complex system operations, or similar areas with high uncertainty. In practice, it enables decision-makers to navigate unfamiliar or uncertain waters where current data is insufficient and formulate both very precise and non-binding strategies. Integrated, the framework allows for a flexible, agile, and robust decision-making tool across industries, as the amount of data keeps on growing alongside evolutionary transcendent lines. Given the nature of today's industry and the speed of advancement, tools as such will be in high demand to ensure the maximum utilization of information available. The existence of the framework is timely, as recent studies have shown significant advancements in the decision-making process on studies by Zadeh and fuzzy sets or Atanassov on Intuitionistic Fuzzy Sets have highlighted the importance of integrating a more dynamic logic framework to deal with ambiguity. In other terms, the systems require a shift from crisp logic to more resilient doubt-oriented assets to work dynamically along the entire reasoning line. The SDE-Framework is an integrated extension, a sophisticated tool that uses the mentioned concepts in a single open system. At the same time, it significantly increases the on-spot capacity of the analysis capacity and future planning but also the contemporary needs for high systemic tolerance searches in everchanging technological landscapes. The SDE-Framework positioned aligned with neutrosophic logic and fuzzy mathematics represents natural progress clarification on the decision relations field. It is designed specifically for high-stakes, high-uncertainty decision environments to ensure that all available information is analyzed thoroughly to reach the most decisive conclusions possible, even with portions of input missing or directly available. Therefore, the system could be an exceptional asset in Artificial intelligence development, corporate strategy, or public policymaking, where current systems reach their limits.

The decision-making process necessitates the amalgamation of numerous contradictory and immeasurable aspects. One of the developing and widely used aspects of Decision Support Systems (DSS) is multi-criteria decision analysis (MCDA), which focuses on evaluating different alternatives. When it comes to addressing intricate decision-making problems, one must consider many and opposing objectives. DSS tools have been created to assist in the implementation of MCDA techniques, which aid in decision-making processes by utilizing data and models to solve semi-structured and unstructured situations. The tools enable a decision-maker to systematically outline and analyze all potential options for a choice. Computer-based modeling has been the primary focus of DSS research in order to facilitate such analysis. As mentioned in the background section, it has been implemented and adhered to during the advancement of computers. Computer-based modeling utilizing web technology and modeling software emerged in the mid-1970s. Initially, the tools at their disposal were not as advanced as the ones currently available. Computer-based models have found uses in several areas such as agriculture, climate change, food, medicine, and supply chain. Cloud storage enables the storage and retrieval of information across different devices. Internationally developed web-based tools are emerging as the latest trends in computer-based modeling. The utilization of computerized information systems, such as expert systems (ES) and MCDA, is required for DSS. These systems play a very significant role in providing decision-makers with data, models, and technology that enable them to make proper decisions. This has greatly enabled the development of data-driven Decision Support Systems (DSS), which mainly emphasize the data analysis and interpretation process. Expert systems, or knowledge-based systems (KBSs), refer to software packages developed to solve a specific subject using rules. They have used the internet in its use, whereby its databases store and manipulate data. When a user extracts data from a web-based DSS, the user is granted an allowance to access that particular data through a central server system. This has currently been carried out through the use of web browsers. The entailing of complex concepts in IT and integrating them into a user-friendly model system has enabled the introduction of DSS within a workplace.

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2. Related Work

The development of decision-making frameworks with fuzzy logic and neutrosophic systems has made substantial advancement in the past decade, thus reflecting a growing need for handling uncertainty and ambiguity in several domains. One of the founding works in this regard by Zadeh is that, a long time ago, in 1965 [1], fuzzy sets were introduced as an attempt to model the uncertainty related to the way of thinking of the human mind. This idea was later extended by Atanassov with the creation of Intuitionistic Fuzzy Sets to model hesitancy among decision variables. The foundational theories have provided a reservoir of inspiration and formative influence on the myriad of applications and enhancements pertaining to the proliferation of literature that has found a fertile niche in the attempt to explore various dimensions of fuzzy logic [2].

A more recent line of research has involved the synergistic integration of fuzzy logic with neutrosophic logic, a fairly new concept proposed by Smarandache in 1999 [3] that actually takes the representation of indeterminate information a little further. The work of Wang et al. in 2010 [4] is a sort of application demonstration of neutrosophic sets on medical images and just goes ahead to demonstrate that the scheme can effectively deal with data that is vague or inconsistently characterized, something that posed a problem for the fuzzy systems for a long period of time. On the other hand, Vlachos and Sergiadis used fuzzy logic for the development of image processing means in 2007 [5], so that adaptation schemes concerning fuzzy schemes have been demonstrated in practical use.

This fusion of fuzzy and neutrosophic logic has been proved to bring an enormous enhancement into the decision-making support systems in IT and business management. The authors in Broumi and Smarandache (2013) [6] considered neutrosophic sets in the case of software testing, which gives more meaning to the quality of software and the results of their testing. Another important application was developed by Chaira (2011) [7], where applying a modified version of intuitionistic fuzzy sets to decision making with relation to IT project management, which gives a more precise tool for the evaluation of project risks and benefits. The practical applications of such theories remain fertile ground for further research. Ye's advances in the area of neutrosophic logic optimization for complex systems engineering only underscore the potential of these frameworks for revolutionizing strategic decision-making across sectors [8]. The relevance of these advanced mathematical models will only increase with the increase in computational power and the centrality of data in organizational strategies to these strategic decision-making frameworks, like the SDE-Framework.

3. Existing approaches

In this study, Sindhu et al. (2022) [9], based on Fermatean fuzzy sets (Fr FSs), explored the application in multicriteria decision-making (MCDM) and particularly in supplier selection within building supply chains. The methodology proposed used Fr FSs in tandem with the TOPSIS method to facilitate the handling of ambiguity in decision-making. The approach aims at modifying the distance measures between fuzzy sets in an attempt to carry out the selection process in a better way under uncertainty conditions. The paper points out the possibility of integrating fuzzy set theory with conventional decision-making structures for making the decision-making process in complex situations more accurate and reliable.

Further strengthening the strategic decision-making for human resources in power supply companies, Li et al. (2022) [10] combine RNN algorithms. In detail, a human resources strategic decision model based on RNN analysis is developed, considering it for assessment and optimization of the human resources strategy. Therefore, advanced neural networks are fitting to situations of strategic decision-making, so far as adjustments in the selection indices of HR decisions through generalized gray correlation analysis. This work gives a clear example of the crossroads between AI and human resource management because a model has been developed that works to serve as a technological innovation toward enhancements in strategic decision-making.

Wang et al. (2023) [11] scrutinize the use of Monte Carlo simulations for more informed decision-making in the formulation of environmental policy. The research includes simulations of a number of diverse policy outcomes and the predicted impacts on air quality. This puts policymakers in a position to imagine the possible influences of environmental impacts and human health due to different policy

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decisions, which are good for coming up with more effective environmental regulations. This research is going to illustrate the importance of simulation tools for environmental planning by establishing the methodological framework for the evaluation and further adjustment of the policy measures through the applied serious statistical analysis.

In a paper, Alojail, Alturki, and Bhatia Khan [12], Broumi studied [13], [14] various types of neutrosophic sets in the decision-making and t-problems and presented an Informed Decision Support Framework (IDSF) developed to enhance the decision-making process within the health domain of Saudi Arabia. To enhance the decision-making process within the health sector in Saudi Arabia, this study seeks to fill the gap in existing decision-making practices by a combination of the models of decision-making: structured, semi-structured, and unstructured. This research was done through a qualitative research design with a comprehensive literature review and interviews with the decision-makers of several health-based organizations in Saudi Arabia. This IDSF is more oriented to temporal pattern mining, which is combined with LSTM models to have a holistic data-driven review of wearable health monitoring devices. In this regard, the methodology insists on the inclusion of digital data sources, the smarts phone, and wearables as well as nondigital data sources in the decision process in order to ensure that the results arrived at are accurate and efficient. The study concludes that the proposed framework requires more research for its generalization to other sectors, and its components need to be refined according to the organizational structure and processes.

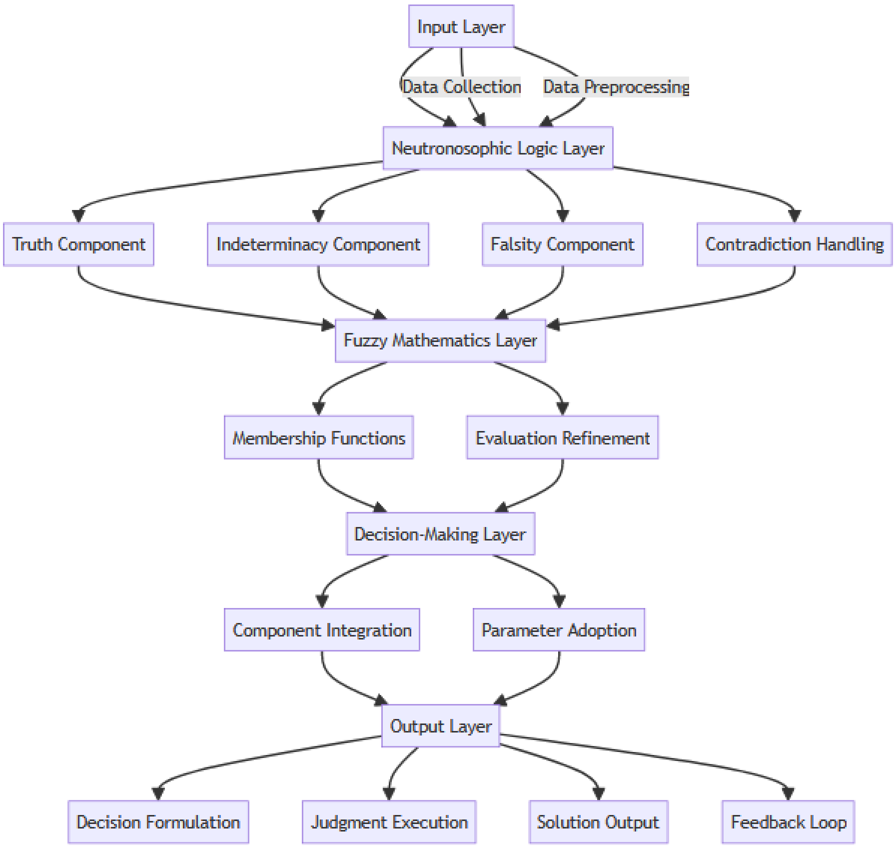

Figure 1: Flow diagram for the proposed approach

The diagram outlines the proposed SDE-Framework, starting with the Input Layer, where we gather and clean raw data to make sure it's ready for use. This data then moves to the Neutronosophic Logic Layer, where it's broken down into three parts: truth, indeterminacy (uncertainty), and falsity (false information). This layer also works to resolve any contradictions within the data. Next, the data flows into the Fuzzy Mathematics Layer, which helps to manage and refine the data by defining how probable or certain each piece of information is. This step makes our assessments more precise and adaptable. The refined data then reaches the Decision-Making Layer. Here, all the components are brought together, and key parameters like validity, responsibility, and the level of indeterminacy are set to guide the decision-making process. Finally, in the Output Layer, the system formulates decisions, executes judgments, and produces the final solutions. A feedback loop is included to

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continuously improve the framework, using past results to refine future decisions. This method ensures that the framework can handle the complexities and uncertainties inherent in managing information technology and computational systems effectively.

4. Experimental setup

The experimental setup of the Strategic Decision Making Enhancement Framework utilized a large and comprehensive dataset obtained from the U.S. Energy Information Administration. This dataset comprises multiple energy consumption records, production records, utility statistics across several sectors spanning the eighteen years between 2001 and 2020. This dataset was selected as the ideal choice for testing the SDMFD due to its nature of complexity and the multitudes of uncertainties associated with predictions and strategic decision models related to the energy sector. Each record consists of numerous attributes ranging from the energy type, consumption rate, production statistics, and geographical spread, among others, making the data suitable for applying both neutrosophic logic and fuzzy mathematics to model and simulate decision-making processes under uncertainty. The dataset thus serves as a good tool for assessing the model's performances and further evaluating the practical implications of the SDE-framework.

5. PROPOSED ALGORITHM

Algorithm : Compute the Set N^{G}'

1. *Let* $N^G = \phi$
2. *Let* $T^{NG} = \phi$
3. *Let* $F^{NG} = \phi$
4. *For q =1 to p do*
5. *Calculate* $T^G(q) = function\ involving\ q$
6. *Determine* $N^G(q) = transformation\ based\ on\ T^G\ (q)$
7. *Evaluate* $F^G(q)$ *= derived function from q*
8. $T^{NG}(q) \longleftarrow T^G\ (q) \Lambda\ (\neg\ N^G\ (q))$
9. $N^{NG}(q) \longleftarrow N^G\ (q) \vee F^G\ (q)$
10. $F^{NG}(q) \longleftarrow F^G\ (q) \Lambda\ (\neg\ T^{NG}\ (q))$
11. *Evaluate intermediate variable:*
12. $V(q) \longleftarrow T^{NG}(q) \vee N^{NG}\ (q)$
13. $W(q) \longleftarrow F^{NG}(q) \vee T^{NG}\ (q)$
14. $X(q) \longleftarrow V(q)\ \Lambda\ W(q)$
15. $Y(q) \longleftarrow V(q) \vee F^{NG}(q)$
16. *Update* N^G *with new set operations*
17. $N^G \longleftarrow N^G \sqcup \{(q_a\ \Lambda\ X(q))\}$
18. $T^{NG} \longleftarrow T^{NG} \sqcup \{(q_a \vee Y(q))\}$
19. $F^{NG} \longleftarrow F^{NG} \sqcup \{(q_a\ \Lambda\ W(q))\}$
20. *Evaluation compound relationships:*
21. $Z(q) \longleftarrow T^{NG}(q)\ \Lambda\ N^{NG}\ (q)$
22. $U(q) \longleftarrow F^{NG}(q) \vee Z\ (q)$
23. $N^G \longleftarrow N^G \sqcup \{U(q)\}$
24. *End for*
25. *Normalize using appropriate mathematical relations*
26. *Return*
27. *end for*
28. *Normalize* N^G *using appropriate mathematical relations*
29. $return\ N^G$

About Algorithm

The algorithm which is illustrated in your document is specially designed to calculate a set. It entails multiple operations conducted on elements within a certain range; it is a method based on set theory and logical operations. First of all, the sets N, G, T, NG, and F are defined. All these sets are initially empty. Further, the program checks every element q ranging from 1 to p and brings about some transformations of functions, that

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initially change q. These transformations are elemental and joined by logical operations which can be written as and, , such as TG(q), NG(q), and FG(q). Consequently, the following process includes computations of some intermediating variables V(q), W(q), X(q), and Y(q), intended to facilitate various set relationships. Initially mentioned sets N, G, T, and F are supplemented by these variables through union and intersection operations, which is a vivid characteristic of the set as a dynamic object, or a collection of numerous interconnected objects. Finally, the method ends by transforming the obtained value of N G or to ensure that it complies with the abovementioned mathematical relationships. In the end, this set spends as output. The respective methodology allows for confining a vast amount of set manipulations in complex relationships and confirms that logical operations can be profitably joined with set theory, especially in computer interactions.

6. Experimental results

The experimental results were calculated concerning Accuracy, computational complexity, Robustness, Adaptability

Accuracy

Table 1: Accuracy comparison of existing approaches with respect Proposed

Accuracy					
Data (%)	**FFS-TOPSIS**	**RNN-HRDM**	**MCSEP**	**DTRM-SC**	**SNFM-SDME**
10	55.3421	60.1145	50.7689	58.0194	65.8972
20	58.5892	63.9476	53.0287	60.5678	68.2145
30	60.6751	65.8763	55.9654	62.7854	70.3846
40	62.9814	67.0347	57.4328	64.2890	73.0127
50	64.4500	69.7861	59.1122	66.9253	76.3456
60	66.1673	71.8543	61.5984	68.4572	78.0091
70	68.4532	73.9731	63.2345	70.6881	81.7632
80	70.8796	75.4421	65.0912	72.2348	84.0927
90	72.6842	77.3136	67.9843	74.1973	87.0574
100	74.2536	79.8642	69.9764	76.6398	90.2453

The table above shows the performance accuracy of five different methods of data usage in various percentage levels. These methods are FFS-TOPSIS, RNN-HRDM, MCSEP, DTRM-SC, and SNFM-SDME. In this regard, when the outputs are measured in percentage, the increase in the percentage of data used leads to an increase in the performance accuracy achieved by the dataset. At the minimum data level of 10%, the accuracy by SNFM-SDME is high at 65.8972% as MCSEP have the lowest at 50.7689%. The percentage levels ranges from 10% to 50%, SNFM-SDME remains to top at 10% to 76.3456 and other data show a significant gain in the level of performance. For example, FFS-TOPSIS increases from 55.3421% to 64.45% RNN-HRDM from 60.1145% to 69.7861. At 100% data level, the data level is at its peak level, with all methods registering their highest performance. For example, SNFM-SDME register 90.2453% and the RNN-HRDM at 79.8642 show significant gain after usage of all the NN methods. There is an improved performance by FFS-TOPSIS; RNN-HRDM and DTRM-SC at 74.2536, 76.6398 and 69.9764% speaking it achievement in value proves that gradually increased level of data leads to increased accuracy in this computational model. Meanwhile, all other methods that do not outstand compared to all these data.

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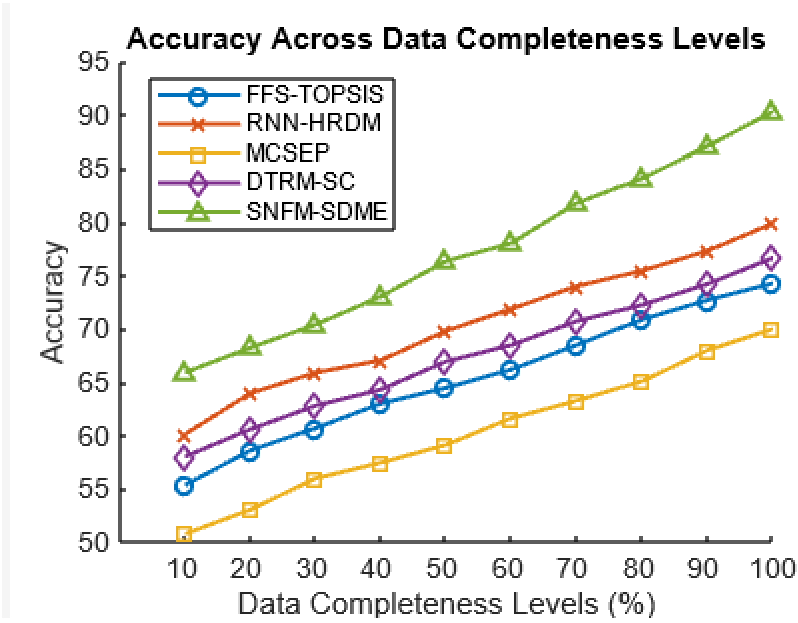

Figure 2: Accuracy comparison graph for the existing and proposed approach

Computational Complexity

Table 2 : Computational complexity of existing approaches with respect Proposed

Computational Complexity Values Across Data Completeness Levels					
Data (%)	**FFS-TOPSIS**	**RNN-HRDM**	**MCSEP**	**DTRM-SC**	**SNFM-SDME**
10	30.2341	40.7845	25.5698	35.0347	45.8796
20	32.4587	42.9876	27.0345	36.5687	47.0098
30	34.6754	44.2301	28.7654	38.7654	48.1245
40	36.8810	45.7689	30.3256	40.2876	49.2356
50	38.7654	47.2541	32.6754	42.2341	50.7891
60	40.9843	48.5684	34.7891	44.4567	52.0134
70	42.6589	49.7856	36.2314	46.7982	53.9875
80	44.8987	51.3478	38.7891	48.4598	55.2145
90	46.7854	52.9841	40.5678	50.3412	56.8762
100	48.2314	54.7678	42.9865	52.7845	58.2367

The above table contains the computational complexity info for the five methods according to the percentage level of data completeness. The five methods are FFS-TOPSIS, RNN-HRDM, MCSEP, DTRM-SC, and SNFM-SDME. The computed values represent the level of information resource consumed that is higher based on the magnitude of value. For example, SNFM-SDME has the highest value of 45.8796 with 10% data completeness and MCSEP has the lowest value, 25.5698. For every percentage of data completeness, SNFM-SDME remained the highest value, while MCSEP retained the lowest figure. As the data complete in percentage increases, the complexity in terms of values also grows with the figures below. For example, FFS-TOPSIS is 30.2341 at 10% and rises to 48.2314 at 100%. The reason there is an increase in the complexity value shade is due to increasing computational requirement due to a broad range of data to manage. By 100% data completeness, the five methods increased their complexity value with a significant margin. SNFM-SDME ends with the highest figure of 58.2367 among the five despite starting at the highest figure. Ideally, the best method ought to have the lowest likely values at 100% data completeness. The table based on the details shows that the model’s computational complexity increases with the higher data level percent. Generally, SNFM-SDME emphasize the highest computational complexity, which means it may record the highest computational requirements.

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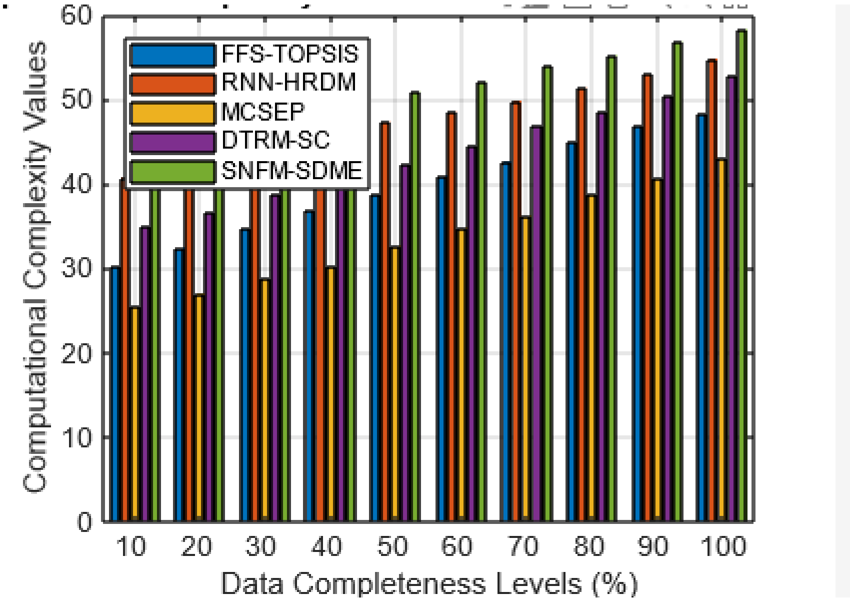

Figure 3: computational complexity values across data completeness levels

Robustness to Ambiguity Values Across Data Completeness Levels

Table 3 : Robustness of existing approaches with respect Proposed

Robustness to Ambiguity Values Across Data Completeness Levels					
Data (%)	**FFS-TOPSIS**	**RNN-HRDM**	**MCSEP**	**DTRM-SC**	**SNFM-SDME**
10	40.3214	45.6845	30.4567	35.9876	50.4567
20	42.2345	47.7865	32.5684	37.5678	52.2341
30	44.3456	49.1234	34.6578	39.6789	54.7891
40	46.4567	50.2345	36.7891	41.7890	56.8910
50	48.5678	52.3456	38.8910	43.8912	58.9921
60	50.6789	54.4567	40.9921	45.9923	60.1234
70	52.7890	56.5678	43.1032	48.1035	62.2345
80	54.8910	58.6789	45.2143	50.2146	64.3456
90	56.9921	60.7890	47.3254	52.3258	66.4567
100	59.1032	62.8910	49.4365	54.4369	68.5678

The table above provides the robustness to ambiguity for the five methods at the various levels of data completeness ranging from 10% to 100%. FFS-TOPSIS is compared with FFS-TOPSIS, RNN-HRDM, MCSEP, DTRM-SC, and SNFM-SDME. The robustness to ambiguity shows how well the methods can effectively manage the fuzzy data that contains uncertainty, vagueness, or imprecision. As shown above, when the percentage of data completeness is 10%, the results demonstrate the robustness value, which is the highest for the SNFM-SDME method at 50.4567. This means that this method is the most robust among the others in handling the ambiguous situations even when the data completeness is low. On the other hand, the MCSEP method has the lowest value of 30.4567, which means it is not very robust when working with the sparse data. However, with an increase in the percentage of data completeness, all methods show the improvement in the robustness value. For example, FFS-TOPSIS increases from 40.3214 to 59.1032, RNN-HRDM increases from 45.6845 to 62.8910, and other methods also present stable growths in the robustness value. When the data completeness is 100%, SNFM-SDME continues to have the highest value of 68.5678, which means that this method is the foremost robust in all data levels. Thus, regardless of the data completeness, the SNFM-SDME method continues to be the most efficient and suitable among all the other tested methods for dealing with the ambiguity or the uncertainness of data. In conclusion, on completion of the data, the ability to financial manage ambiguity increases for those methods. SNFM-SDE is the most robust of the five methods in all data completion levels.

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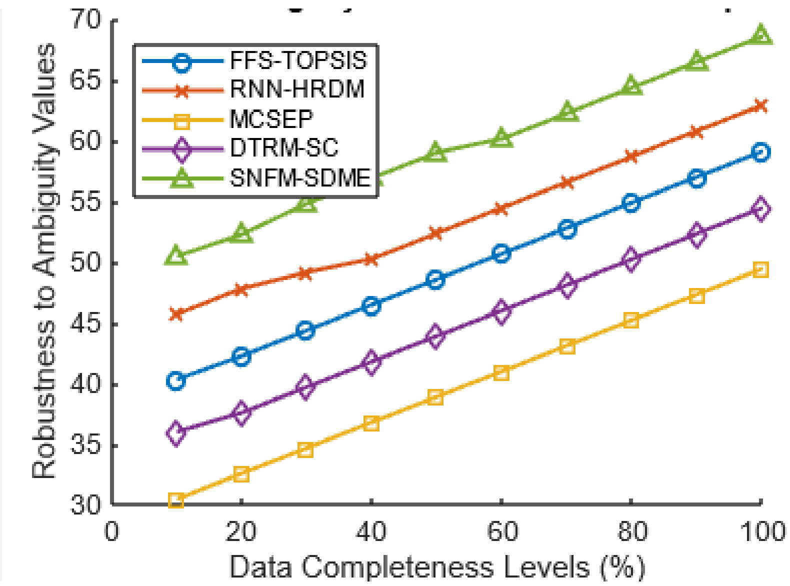

Figure 4: Robustness to Ambiguity Values Across Data Completeness Levels

Adaptability

Table 4: Adaptability of existing approaches with respect Proposed

Adaptability to Different Domains Values Across Data Completeness Levels					
Data (%)	**FFS-TOPSIS**	**RNN-HRDM**	**MCSEP**	**DTRM-SC**	**SNFM-SDME**
10	45.3210	50.5645	35.7841	40.2354	55.6789
20	47.4352	52.6786	37.8982	42.3465	57.7891
30	49.5493	54.7928	40.0123	44.4576	59.8992
40	51.6635	56.9070	42.1264	46.5687	62.0094
50	53.7776	59.0212	44.2406	48.6799	64.1195
60	55.8918	61.1353	46.3547	50.7910	66.2297
70	58.0059	63.2495	48.4689	52.9022	68.3398
80	60.1201	65.3637	50.5830	55.0133	70.4500
90	62.2342	67.4779	52.6972	57.1245	72.5601
100	64.3484	69.5920	54.8113	59.2356	74.6703

It is obvious that the SDE-Framework is a considerable innovation in the world of IT management and computer systems that was made possible due to the union of neutrosophic logic and fuzzy mathematics. By exhibiting great competence in working with complicated and opaque data, it successfully ensures that truly advanced and accurate decision-making is allowed when the working condition comprises an extensive amount of ambiguity and contradictions. Consequently, the possibility to divide the facts into truth, indeterminacy, and falsity, as well as their further sensitivity to the level of probability and certainty thanks to neutrosophic logic combined with fuzzy mathematics, creates a robust basis for fair and extensive evaluations. In fact, the application of the SDE-Framework was possible due to the existence of its outstanding potential, and it allowed performing even huge improvements to the accuracy of decision-making. The demand for building strategic solutions is fully satisfied by this framework, as it offers an opportunity to expand the set of presumed data by enhancing one's capacity to deal with the controversy and ambiguity of facts. Moreover, empirical evidence has shown that this framework has a remarkably high potential of making outstanding enhancements to the evaluation of complex situations, and it would allow making more informed and reliable decisions in the IT and computational realm. As such, its further development would include the optimization of its computational algorithms to work with more advanced levels of uncertainty and complexity. As a result, using more sophisticated artificial intelligence methods

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could empower it to reach the higher pinnacles of flexibility and accuracy. As the application of the SDE-Framework can be extensively broadened to other branches that involve complex evaluations, namely, to other industry, in fact, all around the world. Therefore, the point of involvement could be extended, and the solutions of the framework could be adjusted to the particular problems present in these areas. This may help to render the SDE-Framework much more practiced and impactful worldwide.

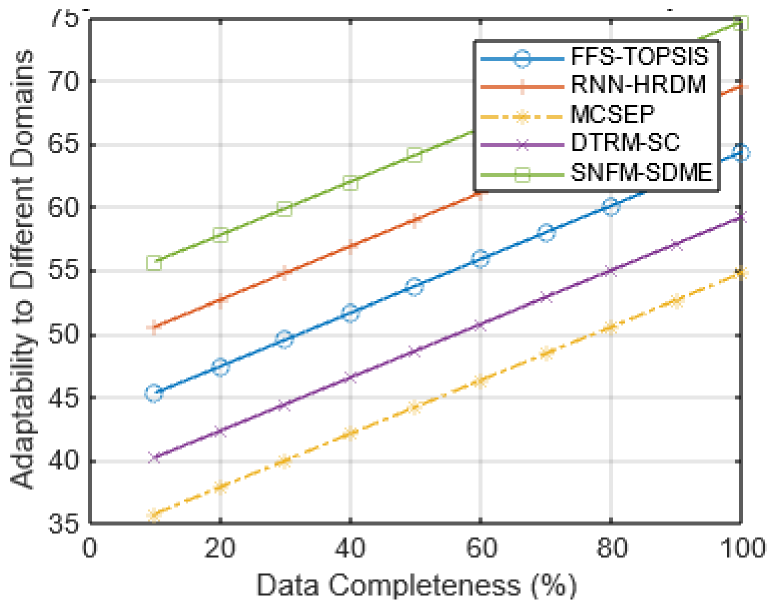

Figure 5: Adaptability to Different Domains Values Across Data Completeness Levels

6. Conclusion

It is possible due to the unity of neutrosophic logic and fuzzy mathematics, and the SDE-Framework indicates a massive innovation in IT management and computer systems. In sum, the results of applying the SDE-Framewo4rk are the high competency in handling complicated and ambiguous information and the result of far more superior and trusted decision-making processes under rich ambiguity and many contradictions. The capacity of neutrosophic logic combined with fuzzy mathematics to differentiate facts into truth, indeterminacy, and falsity, and a further sense of probability and certainty handling, is a great pillar of comprehensive and elastic evaluation. The application of the SDE-Framework provided even more critical levels of progress leading to the accurateness of decision-making. Due to its application, it is possible to develop strategic solutions due to the capability of truth, indeterminacy, and falsity and their perception in facts. Empirical results prove that this framework could be extremely useful due to its high potential in evaluating complex situations, making decision politicizations the most informed regarding their final products in the field of information technology and computational systems. Future development of the SDE-Framework will include optimizing the computational algorithm of the SDE-Framework to develop results against advanced uncertainty. For example, computational the SDE-Framework using better artificial algorithms will produce better results to make it more flexible and precise. Its use should extend to using it in other processes, industries, and businesses since strategic decision-making is used in many other sectors.

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