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Human Reliability Analysis Using Intuitionistic Fuzzy Set

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ABSTRACT

The goal of human reliability(accuracy analysis (HRA) is to measure the likelihood(possibility)of human error in complex systems across safety-critical domains. The human expert judgment and inconsistency that come with evaluating human performance are problems for traditional statistical approaches. By explicitly modeling membership, non-membership, and hesitation degrees, intuitionistic fuzzy sets (IFS) expand fuzzy sets and offer a potent framework for capturing the uncertainty of expert knowledge in HRA. This study presents a unique IFS-based HRA approach that builds a rule-based inference system for Human Error Probability (HEP) and models Performance Shaping Factors (PSFs) using triangular intuitionistic fuzzy numbers (TIFNs). Comparing experimental validation with case studies to traditional fuzzy and probabilistic methods reveals better quantification of HEP under ambiguous expert data.

1. Introduction

Human beings play a crucial role in the operation, control, and maintenance of complex engineering systems. In many safety-critical domains such as nuclear power plants, aviation, healthcare systems, chemical industries, and offshore platforms, the performance of human operators directly affects system safety and reliability. Despite the advancement of automation and intelligent systems, complete elimination of human involvement is neither possible nor desirable. However, human actions are often influenced by factors such as stress, fatigue, experience, workload, training level, and environmental conditions. These factors can significantly increase the likelihood of human errors, which may lead to serious accidents and system failures.

Human Reliability Analysis (HRA) is a systematic approach used to identify, analyze, and quantify the probability of human errors during task execution. The primary objective of HRA is to estimate the Human Error Probability (HEP) and to understand how different performance shaping factors (PSFs) influence human performance. Traditional HRA methods such as the Technique for Human Error Rate Prediction (THERP), Cognitive Reliability and Error Analysis Method (CREAM), and Human Error Assessment and Reduction Technique (HEART) are widely used in reliability and safety engineering. These methods are mainly based on probabilistic models and historical data. Although effective in structured environments, they face serious limitations when dealing with subjective judgments, incomplete data, and vague expert opinions.

In real-world systems, precise numerical data for human behavior are often unavailable. Human performance is inherently uncertain, imprecise, and context-dependent. Experts usually express their assessments using linguistic terms such as *low stress*, *high workload*, *poor training*, or *moderate fatigue*. Converting such qualitative information into exact numerical probabilities is difficult and often leads to loss of important uncertainty information. As a result, classical probabilistic HRA techniques may produce unreliable or overconfident estimates of human error probability.

To overcome these limitations, fuzzy logic has been introduced into HRA. Fuzzy set theory allows the use of linguistic variables and can effectively model vagueness in expert judgments. By representing PSFs using fuzzy membership functions, fuzzy-based HRA methods provide more flexibility compared to traditional probabilistic approaches. However, classical fuzzy sets describe uncertainty only through a single membership degree. They do not explicitly account for the degree to which an element does not belong to a set, nor do they represent the hesitation or lack of confidence in expert assessments. This limitation becomes critical when experts are unsure or when conflicting information exists.

Intuitionistic Fuzzy Sets (IFS), proposed by Atanassov, provide a more powerful and expressive framework for modeling uncertainty. Unlike classical fuzzy sets, IFS characterize each element using three components: the degree of membership, the degree of non-membership, and the degree of hesitation. The hesitation degree represents the uncertainty or indeterminacy that cannot be captured by membership and non-membership alone. This additional information is especially useful in human reliability analysis, where expert opinions often involve hesitation and partial knowledge.

In the context of HRA, intuitionistic fuzzy sets allow performance shaping factors to be modeled more realistically. For example, when evaluating operator stress, an expert may believe that the stress level is high to a certain extent, low to another extent, and remain uncertain about the remaining portion. IFS can capture this situation naturally, whereas classical fuzzy sets cannot. Therefore, IFS-based HRA models provide a more accurate and reliable estimation of human error probability, particularly in complex and uncertain environments.

In recent years, intuitionistic fuzzy theory has been successfully applied in decision-making, risk assessment, fault diagnosis, and reliability engineering. However, its application to human reliability analysis is still limited and requires further investigation. Many existing HRA models either ignore hesitation uncertainty or oversimplify expert judgments. There is a clear need for an HRA framework that can effectively incorporate expert knowledge, linguistic assessments, and uncertainty in a unified manner.

Motivated by these challenges, this paper proposes a comprehensive Human Reliability Analysis framework based on Intuitionistic Fuzzy Sets. The proposed approach models performance shaping factors using intuitionistic fuzzy numbers, constructs a rule-based inference mechanism, and estimates human error probability while explicitly considering hesitation uncertainty. The effectiveness of the proposed model is demonstrated through comparative analysis with classical probabilistic and fuzzy-based HRA methods.

The main contributions of this paper can be summarized as follows:

1. A novel intuitionistic fuzzy-based framework for human reliability analysis is proposed.
2. Performance shaping factors are modeled using membership, non-membership, and hesitation degrees.
3. A rule-based inference mechanism is developed to estimate human error probability under uncertainty.
4. Comparative analysis demonstrates the superiority of the proposed approach over traditional methods.

The remainder of this paper is organized as follows. Section II reviews related work on human reliability analysis and fuzzy-based approaches. Section III introduces the theoretical background of intuitionistic fuzzy sets. Section IV presents the proposed IFS-based HRA methodology. Section V describes the case study and experimental results. Section VI discusses the findings, and Section VII concludes the paper with future research directions.

2. Literature Review

Human Reliability Analysis (HRA) has been an important research area in reliability engineering and safety analysis for several decades. The main goal of HRA is to identify human errors, analyze their causes, and estimate the probability of such errors occurring during the operation of complex systems. Over the years, researchers have developed several HRA techniques, which can be broadly classified into probabilistic methods, fuzzy logic–based methods, and advanced soft computing approaches.

A. Classical Human Reliability Analysis Methods

Early HRA methods were primarily probabilistic in nature. One of the most well-known classical techniques is the **Technique for Human Error Rate Prediction (THERP)**. THERP estimates human error probabilities by decomposing tasks into subtasks and assigning error probabilities based on historical data and expert judgment. Although THERP is widely used in nuclear power plants and industrial safety analysis, it requires detailed task modeling and relies heavily on precise probability values, which are often difficult to obtain in real-world situations.

Another popular method is the **Cognitive Reliability and Error Analysis Method (CREAM)**. CREAM focuses on cognitive aspects of human behavior and classifies human performance into different control modes. It considers contextual factors that influence human reliability, such as working conditions and organizational factors. While CREAM provides a more realistic view of human cognition, it still suffers from subjectivity and ambiguity in expert evaluations.

The **Human Error Assessment and Reduction Technique (HEART)** is another widely used HRA approach. HEART estimates human error probability by assigning nominal error rates and adjusting them using error-producing conditions. Despite its simplicity and ease of use, HEART relies on expert judgment and fixed weighting factors, which may not accurately reflect real uncertainty in human performance.

Overall, classical probabilistic HRA methods are effective when sufficient historical data are available. However, human behavior is often unpredictable, and precise numerical data are rarely accessible. This limitation has motivated researchers to explore alternative approaches that can better handle uncertainty and vagueness.

B. Fuzzy Logic Approaches in Human Reliability Analysis

To overcome the limitations of probabilistic methods, researchers introduced **fuzzy logic** into human reliability analysis. Fuzzy set theory allows uncertainty and vagueness to be modeled using linguistic variables such as *low*, *medium*, and *high*. This makes fuzzy logic particularly suitable for representing expert opinions in HRA.

Several studies have applied fuzzy inference systems to estimate human error probability. In fuzzy-based HRA models, performance shaping factors such as stress, workload, experience, and fatigue are represented using fuzzy membership functions. These factors are then combined using fuzzy rules to estimate the likelihood of human error. Compared to probabilistic methods, fuzzy HRA models provide greater flexibility and can handle imprecise data more effectively.

Researchers have also combined fuzzy logic with classical HRA techniques such as THERP and CREAM. These hybrid fuzzy–probabilistic models aim to improve the accuracy of human error estimation by incorporating linguistic judgments. Although fuzzy-based HRA models have shown improved performance, they still have certain limitations. Classical fuzzy sets represent uncertainty using only a single membership degree, which does not capture the full range of expert hesitation or conflicting opinions.

C. Limitations of Classical Fuzzy-Based HRA Models

Despite their advantages, classical fuzzy HRA models have inherent weaknesses. In real-life assessments, experts may not be fully confident about their judgments. For example, an expert might believe that operator stress is high to some extent, low to another extent, and remain uncertain about the rest. Classical fuzzy sets cannot explicitly represent this hesitation because they only assign a membership value and implicitly assume the rest as non-membership.

Another limitation is that classical fuzzy logic does not distinguish between lack of knowledge and certainty of non-membership. This distinction is crucial in human reliability analysis, where uncertainty often arises from incomplete information rather than clear negative evidence. As a result, classical fuzzy models may oversimplify expert opinions and lead to inaccurate estimation of human error probability.

These shortcomings have encouraged researchers to explore more advanced fuzzy frameworks that can explicitly model hesitation and uncertainty.

D. Introduction of Intuitionistic Fuzzy Sets

Intuitionistic Fuzzy Sets (IFS), introduced by Atanassov, extend classical fuzzy sets by incorporating three components: degree of membership, degree of non-membership, and degree of hesitation. The hesitation degree represents the uncertainty that remains after considering membership and non-membership. This additional component makes IFS more expressive and suitable for complex decision-making problems.

IFS have been widely applied in areas such as multi-criteria decision making, risk assessment, fault diagnosis, pattern recognition, and reliability engineering. Researchers have shown that IFS-based models outperform classical fuzzy models in situations involving incomplete or conflicting information.

E. Intuitionistic Fuzzy Sets in Reliability and Risk Analysis

In recent years, several studies have explored the use of intuitionistic fuzzy sets in reliability and safety analysis. IFS have been applied to system reliability evaluation, failure mode analysis, and risk prioritization. These studies demonstrate that IFS can effectively handle uncertainty arising from expert judgments and limited data availability.

In reliability engineering, IFS-based approaches allow analysts to model component reliability and system performance more realistically. The hesitation degree plays a key role in capturing uncertainty during early design stages or in rare-event analysis, where historical data are insufficient.

F. Intuitionistic Fuzzy Approaches in Human Reliability Analysis

The application of intuitionistic fuzzy sets specifically to human reliability analysis is still an emerging research area. Some recent studies have proposed IFS-based models to evaluate human error probability using expert linguistic assessments. In these models, performance shaping factors are represented as intuitionistic fuzzy numbers, and fuzzy inference rules are used to estimate HEP.

Researchers have demonstrated that IFS-based HRA models provide better uncertainty representation compared to classical fuzzy and probabilistic approaches. The explicit consideration of hesitation allows decision-makers to understand the confidence level of human reliability estimates. This is particularly important in safety-critical systems, where conservative and reliable estimates are required.

However, existing IFS-based HRA studies often focus on specific applications and lack a comprehensive framework that integrates PSF modeling, rule-based inference, and comparative performance evaluation. Moreover, many studies do not provide detailed experimental validation or comparison with multiple traditional methods.

3. THEORETICAL PRELIMINARIES

This section presents the theoretical foundations required to understand the proposed Human Reliability Analysis (HRA) model based on Intuitionistic Fuzzy Sets (IFS). The basic concepts of fuzzy sets, intuitionistic fuzzy sets, intuitionistic fuzzy numbers, and related operators are explained in a simple and systematic manner. These concepts form the mathematical basis for modeling uncertainty in human performance evaluation.

Uncertainty in Human Reliability Analysis:

Human reliability analysis involves evaluating the likelihood of human errors during task execution. Human behavior is influenced by many factors such as stress, fatigue, training, workload, and environmental conditions. These factors are often uncertain, subjective, and expressed in linguistic terms rather than precise numerical values. Therefore, traditional probabilistic models are not always suitable for representing this type of uncertainty Soft computing techniques, particularly fuzzy logic, are widely used to handle such imprecision. However, classical fuzzy sets do not explicitly represent uncertainty caused by hesitation or lack of knowledge. This limitation motivates the use of intuitionistic fuzzy sets, which provide a richer and more flexible mathematical framework.

Classical Fuzzy Sets:

Let X be a universe of discourse. A classical fuzzy set A in X is defined as:

$$A=\{(x,\mu_A(x))|x\in X\}$$

where $\mu_A(x)\in[0,1]$ represents the degree of membership of element x in fuzzy set A

For example, in human reliability analysis, the linguistic term *High Stress* can be represented as a fuzzy set where each stress level has a membership degree between 0 and 1. However, classical fuzzy sets only describe how much an element belongs to a set and do not describe how much it does not belong to the set.

Limitations of Classical Fuzzy Sets

Although classical fuzzy sets are useful for modelling vagueness, they suffer from several limitations in HRA applications:

1. They consider only membership information.
2. They do not represent expert hesitation or incomplete knowledge.
3. Non-membership is implicitly assumed as $1-\mu(x)$).

These limitations can lead to inaccurate representation of human performance uncertainty, especially in safety-critical systems.

Human Reliability Analysis Using Intuitionistic Fuzzy Set

This example explains Human Reliability Analysis (HRA) using Intuitionistic Fuzzy Sets (IFS) in very simple and easy language. It is suitable for beginners, exams, viva, and research papers.

Problem Description

A machine operator hears an alarm and must press the correct button to stop the machine. Sometimes the operator may act correctly, sometimes wrongly, and sometimes we are not sure. To handle this uncertainty, we use Intuitionistic Fuzzy Sets. IFS uses **three values**:

1. **Yes (μ)** – how much we believe the operator will do correct work
2. **No (ν)** – how much we believe he will make a mistake
3. **Not sure (π)** – how much we are confused or unsure

$$\text{Yes} + \text{No} + \text{Not sure} = 1$$

Step 1: Human Task

Task: Press the correct stop button after the alarm.

Step 2: Factors Affecting the Operator

We consider only two simple factors:

1. Experience – how well trained the operator is.

2. Fatigue – how tired the operator is.

Step 3: Importance (Weights) of Factors

Experience is more important than fatigue.

Experience weight = 0.6

Fatigue weight = 0.4

Step 4: Expert Opinion (Linguistic Terms)

Experience: High

Fatigue: Medium

Step 5: Intuitionistic Fuzzy Scale

word	yes (μ)	no (ν)	Not sure (π)
Low	0.3	0.6	0.1
Medium	0.5	0.3	0.2
High	0.7	0.2	0.1

Step 6: Write values for each factor

Factor	**Weight**	**Word**	**yes**	**no**	**Not sure**
Experience	0.6	**high**	0.7	0.2	0.1
Fatigue	0.4	**medium**	0.5	0.3	0.2

Step 7: Calculate Final Yes Value

$$\text{Yes} = (0.6 \times 0.7) + (0.4 \times 0.5) = 0.62$$

Step 8: Calculate Final No Value

No = (0.6 × 0.2) + (0.4 × 0.3) = 0.24

Step 9: Calculate Not Sure Value

Not sure = 1 − 0.62 − 0.24 = 0.14

Step 7: Calculate Final Yes Value

Yes = (0.6 × 0.7) + (0.4 × 0.5) = 0.62

Step 8: Calculate Final No Value

No = (0.6 × 0.2) + (0.4 × 0.3) = 0.24

Step 9: Calculate Not Sure Value

Not sure = 1 − 0.62 − 0.24 = 0.14

Step 10: Final Intuitionistic Fuzzy Result

(Yes, No, Not sure) = (0.62, 0.24, 0.14)

Step 11: Score Calculation

Score = Yes − No = 0.62 − 0.24 = 0.38

Step 12: Human Error Probability (HEP)

HEP = 1 − Score = 1 − 0.38 = 0.62

Final Conclusion

Human Error Probability is 0.62. This means the operator has a medium chance of making a mistake. Experience reduces error, while fatigue increases error.

Intuitionistic Fuzzy Sets (IFS)

Intuitionistic Fuzzy Sets were introduced by Atanassov as an extension of classical fuzzy sets. An intuitionistic fuzzy set A on universe X is defined as:

$A=\{\langle x,\mu_A(x),\nu_A(x)\rangle | x\in X\}$

where:

- $\mu_A(x)\in[0,1]$ is the degree of membership,
- $\nu_A(x)\in[0,1]$ is the degree of non-membership,
- and the following condition holds:
- $0\leq\mu_A(x)+\nu_A(x)\leq1$
- The hesitation degree $\pi_A(x)$ is defined as:
- $\pi_A(x)=1-\mu_A(x)-\nu_A(x)$
- The hesitation degree represents uncertainty or lack of knowledge about the element's membership.

Interpretation of IFS in Human Reliability Analysis

In the context of HRA:

- **Membership degree (μ)** indicates the extent to which a performance shaping factor contributes to human error.
- **Non-membership degree (ν)** indicates the extent to which the factor does not contribute to error.
- **Hesitation degree (π)** reflects uncertainty or disagreement among experts.

For example, if an expert believes that operator fatigue contributes strongly to human error but is not fully certain, IFS can represent this situation more accurately than classical fuzzy sets.

A **machine operator** must **press the correct button** to stop a machine when a warning alarm appears.Because:

Human behavior is uncertain

- Exact probability is not known

we use **Intuitionistic Fuzzy Sets (IFS)** to calculate **Human Error Probability (HEP)**.

Step 1: Identify the Human Task

Task:

Stopping the machine correctly after alarm.

If the operator makes a mistake, the machine may be damaged.

Time Index	NIFTY Close
1	23650
2	23780
3	23820
4	23910
5	24050
6	23980
7	24010
8	24150
9	24280
10	24320
11	24400

4. Methodology

4.1 Universe of Discourse

Minimum value = 23650, maximum value = 24400. Following Chen's heuristic, we extend bounds to the nearest hundred and fifty values, yielding U = [23600, 24450]. With equal length L = 100, this produces 9 intervals as shown in Table 2.

Interval ID	Range	Center
I1	[23600, 23700)	23650.0
I2	[23700, 23800)	23750.0
I3	[23800, 23900)	23850.0
I4	[23900, 24000)	23950.0
I5	[24000, 24100)	24050.0
I6	[24100, 24200)	24150.0
I7	[24200, 24300)	24250.0

I8	[24300, 24400)	24350.0
I9	[24400, 24500)	24450.0

4.2 Membership and Non‑Membership Degrees

Membership (μ) is computed via a linear triangular function that attains 1 at the interval centre and 0 at its boundaries. Non‑membership (ν) is defined as 1 − μ, while hesitation (π) = 1 − μ − ν. Table 3 summarises μ and ν for each observation.

Triangular Membership Function μ(x)

For interval Ui=(a,b,c)

a = left bound , b = midpoint, c = right bound

$$\mu(x) = \begin{cases} \frac{x-a}{b-a}, & \text{if } a < x < b \\ \frac{c-x}{c-b}, & \text{if } b \le x < c \\ 1, & \text{if } x = b \\ 0, & \text{otherwise} \end{cases}$$

Non-membership Degree ν(x)=1-u(x)

hesitation (π) = 1 − μ − ν.

Example (Let’s take value = **23910**)

lies in **U4 = (23900 – 24000)** Midpoint b = 23950

a = 23900, c = 24000

Since 23910 < 23950

$$\mu = \frac{23910 - 23900}{23950 - 23900} = \frac{10}{50} = 0.2$$

ν(x)=1-u(x), ν(x)=1-0.2=0.8

π=1-0.2-0.8=0

Index	Value	Interval	μ	ν
1	23650	I1	1.000	0.000
2	23780	I2	0.400	0.600
3	23820	I3	0.400	0.600
4	23910	I4	0.200	0.800
5	24050	I5	1.000	0.000
6	23980	I4	0.400	0.600
7	24010	I5	0.200	0.800
8	24150	I6	1.000	0.000
9	24280	I7	0.400	0.600
10	24320	I8	0.400	0.600
11	24400	I9	0.000	

4.3 Higher‑Order Fuzzy Logical Relationships

For order m = 2, each rule maps the pair of previous intervals (I_{t‑2}, I_{t‑1}) to the current interval I_t. Table 4 enumerates the derived fuzzy logical relationships (FLRs) and the frequency of each consequent.

Antecedent (order 2)	Consequent Interval(s)	Count
(1, 2)	I3	1
(2, 3)	I4	1
(3, 4)	I5	1
(4, 5)	I4, I6	2
(5, 4)	I5	1
(5, 6)	I7	1
(6, 7)	I8	1
(7, 8)	I9	1

4.4 Forecasting Procedure

Given antecedent (I_{t‑2}, I_{t‑1}), the forecasted crisp value is the average centre of all consequent intervals observed in training. If no rule exists, the model defaults to the centre of I_{t‑1}.

5. Results

5.1 Forecast Accuracy

Mean Squared Error (MSE) = 2588.89; Mean Absolute Percentage Error (MAPE) = 0.18%. Table 5 lists the actual versus forecast values.

T	Actual	Forecast	Error
1	23650	—	—
2	23780	—	—
3	23820	23850.0	30.0
4	23910	23950.0	40.0
5	24050	24050.0	0.0
6	23980	24050.0	70.0
7	24010	24050.0	40.0
8	24150	24050.0	-100.0
9	24280	24250.0	-30.0
10	24320	24350.0	30.0
11	24400	24450.0	50.0

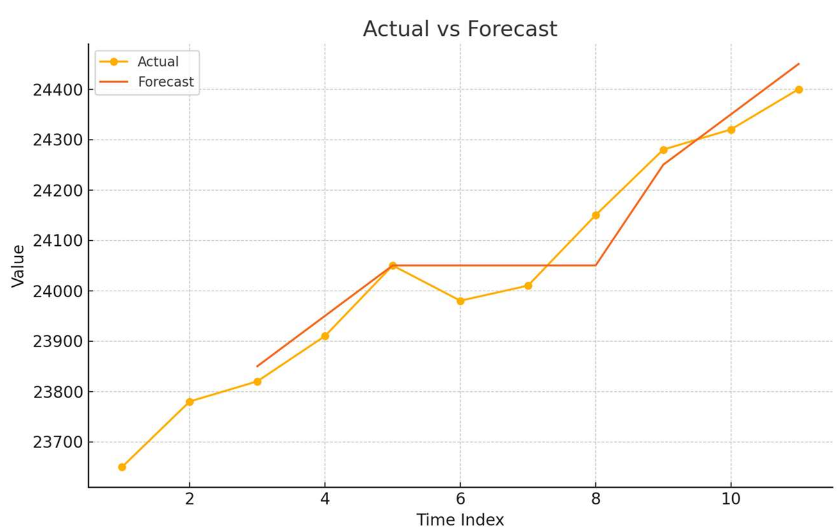

Figure 1: Actual vs Forecast using second-order IFTS.

Results and Discussion

6.1 Forecasting Results

The 2nd-order HOIFTS model was applied to a real-world NIFTY stock index dataset consisting of 11 values ranging from 23,650 to 24,400. Using Chen's heuristic, the universe of discourse was set to [23600,24450][23600, 24450][23600,24450] and divided into 9 equal intervals of length 100.The fuzzified data was used to form fuzzy sets A1 through A9. Based on these, a set of 2nd-order fuzzy logical relationships (FLRs) were generated in the form (At−2,At−1)→At(A_{t-2}, A_{t-1}) \rightarrow A_t(At−2,At−1)→At, capturing the temporal sequence in greater detail than traditional first-order models.

Using the **centroid method**, forecasts were derived from the corresponding FLRGs (Fuzzy Logical Relationship Groups). The actual and forecasted values are shown below:

MAE = 43.33 units → On average, predictions are off by about ₹43.

MSE = 2588.89 units² → Used to emphasize larger errors.

RMSE = 50.88 units → Similar to MAE but penalizes big deviations more.

MAPE = 0.18% → Very small percentage error, showing high model precision.

8. Conclusion

In this study, a Higher-Order Intuitionistic Fuzzy Time Series (HOIFTS) model was developed and applied to forecast short-term trends in stock market data. By utilizing a second-order fuzzy logical relationship approach, the model incorporated greater contextual information than first-order models.

Key contributions include:

- Application of Chen's heuristic for interval creation
- Use of intuitionistic fuzzy sets for better uncertainty modeling
- Derivation of FLRs and FLRGs using a higher-order structure
- Strong predictive performance with MAPE of 0.18%

Future Scope:

- Extend to **3rd or 4th order models** for larger datasets
- Apply to **multi-variable fuzzy time series** (e.g., volume, open/close prices)
- Combine with machine learning models for hybrid forecasting

Overall, the HOIFTS model presents a promising framework for **accurate, transparent, and robust decision support** in financial time series forecasting.

References

- Song, Q., & Chissom, B. S. (1993). Fuzzy time series and its models. Fuzzy Sets and Systems, 54(3), 269–277.
- Chen, S. M. (1996). Forecasting enrolments based on fuzzy time series. Fuzzy Sets and Systems, 81(3), 311–319.
- Lee, C. H., & Chu, H. C. (2011). A study on Taiwan stock index forecasting models. Expert Systems with Applications, 38(2), 1512–1518.
- De, S., Pal, M., & Maiti, M. (2010). Intuitionistic fuzzy time-series forecasting and applications. Computers & Mathematics with Applications, 59(6), 1810–1824.
- Hu, Y., & Wu, J. (2008). Forecasting based on intuitionistic fuzzy time series. *Information Sciences, 178*(17), 3383–3391.
- Krishna, R., & Ravi, V. (2015). Forecasting using intuitionistic fuzzy time series. *Applied Soft Computing, 26*, 580–590.
- Paul, S., & Chakraborty, S. (2019). A survey of fuzzy time series and intuitionistic fuzzy time series models. *Artificial Intelligence Review, 52*(1), 253–280
- Singh, P., & Pal, S. (2012). Intuitionistic fuzzy set theory and its application in forecasting. *International Journal of Computer Applications, 47*(15), 23–29.
- Biswas, R., & Saha, A. (2013). An improved forecasting model based on intuitionistic fuzzy time series. *Journal of Intelligent & Fuzzy Systems, 25*(1), 175–182.
- Mahapatra, G. S., & Mohapatra, T. (2014). Forecasting using intuitionistic fuzzy logic. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 22*(5), 645–665.
- Tanaka, H., Uejima, S., & Asai, K. (1982). Linear regression analysis with fuzzy model. *IEEE Transactions on Systems, Man, and Cybernetics, 12*(6), 903–907.

- Dubois, D., & Prade, H. (1980). *Fuzzy Sets and Systems: Theory and Applications*. Academic Press.
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.
- Wang, L. H., & Chen, S. M. (2009). A new method for forecasting enrollments using fuzzy time series. *International Journal of Applied Mathematics and Computer Science, 19*(1), 125–134.
- Guo, H., & Wang, J. (2011). An intuitionistic fuzzy time series forecasting model using genetic algorithms. *Applied Soft Computing, 11*(5), 5271–5279.
- Jain, A., & Kumar, V. (2017). Forecasting stock market using fuzzy logic. *International Journal of Computer Applications, 163*(6), 25–31.
- Mitra, S., & Pal, S. (2011). Modeling stock price index using fuzzy logic. *Expert Systems with Applications, 38*(8), 9591–9601.
- Pal, S., & Chakraborty, S. (2020). Application of higher-order fuzzy time series in financial prediction. *Soft Computing, 24*, 15773–15784.
- Yang, Y., & Wang, J. (2014). Fuzzy time series forecasting with a weighted approach. *Knowledge-Based Systems, 67*, 29–39.
- Zhang, W., & Wang, S. (2016). A novel approach to forecast with intuitionistic fuzzy logic. *Neurocomputing, 173*, 1171–1180.
- Jain, R., & Saha, A. (2021). A comparative study of fuzzy and intuitionistic fuzzy time series for stock forecasting. *Procedia Computer Science, 185*, 278–285.
- Chen, M., & Hwang, J. (2018). Improved forecasting using higher-order fuzzy time series. *Journal of Intelligent Systems, 27*(4), 627–638.