



A Hesi Tant Fuzzy Set-Based Framework for Human Reliability Analysis and Stock-Market Time-Series Forecasting

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DOI : <https://doi.org/10.5281/zenodo.23768434>

ARTICLE DETAILS

Research Paper

Received: 28-08-2026

Accepted: 24-09-2026

Published: 20-10-2026

Keywords:

Hesitant fuzzy sets; human reliability analysis; human error probability; performance-shaping factors; fuzzy time series; NIFTY; uncertainty; forecasting.

ABSTRACT

This paper develops a hesitant fuzzy set (HFS)-based framework for two uncertainty-sensitive applications: (i) human reliability analysis (HRA), with emphasis on human error probability (HEP), and (ii) short-term stock-market time-series forecasting using NIFTY closing values. Unlike an intuitionistic fuzzy set, which uses one membership degree and one non-membership degree subject to a constraint, an HFS represents an element by a finite set of plausible membership values. This is useful when several experts or assessment procedures provide different degrees of support and no single value adequately represents their judgment. For HRA, the framework represents uncertainty in performance-shaping factors such as experience, fatigue, stress, and workload through hesitant membership values and aggregates factor-level assessments using stated weights. For forecasting, the original NIFTY observations and interval partition are retained as source data, while a proposed HFS encoding and rule-based forecasting workflow are specified. The supplied paper's original IFS/FTS numerical outputs are not presented as validated HFS results: membership assignments, hesitant aggregation, rule construction, forecasts, and error metrics require recalculation from a fully specified HFS model. The contribution of this converted draft is therefore a reproducible model specification and an explicit validation plan, rather than an unsupported claim of

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improved accuracy.

1. Introduction

Human judgments and financial observations may involve vagueness, disagreement, and incomplete information. In HRA, an expert may judge fatigue as a moderate contributor to error while another expert gives a higher assessment. In financial forecasting, a price observation near a boundary between intervals may be interpreted differently by alternative membership functions or expert assessments. A model should retain these differences rather than prematurely reducing them to one number.

Classical fuzzy sets represent membership by a single value. Intuitionistic fuzzy sets add non-membership and an implied hesitation component. Hesitant fuzzy sets (HFS), introduced to model situations where decision-makers hesitate among several possible membership degrees, instead represent membership by a set of values. The two approaches are related but not interchangeable.

This converted draft proposes a common HFS foundation and then applies it independently to HRA and NIFTY forecasting. The HRA part defines a hesitant representation for performance-shaping factors and a transparent weighted aggregation procedure. The forecasting part retains the eleven NIFTY observations and the universe of discourse in the supplied paper, and sets out the HFS fuzzification, rule extraction, defuzzification, and evaluation steps that must be implemented to obtain defensible results.

2. Research objectives and contributions

1. To define HFS notation and aggregation operations suitable for uncertain expert judgments.
2. Specify an HFS-based HRA workflow for performance-shaping factors and human error probability.
3. Specify an HFS-based time-series forecasting workflow using the NIFTY observations in the source paper.
4. Separate source-derived data from proposed modelling choices and unvalidated outputs.
5. Provide a validation plan for comparing HFS results with classical fuzzy, IFS, and baseline forecasting methods.

3. Hesitant fuzzy sets:

3.1 Definition

Let X be a universe of discourse. A hesitant fuzzy set A on X can be written as $A = \{ \langle x, h_A(x) \rangle : x \in X \}$, where $h_A(x)$ is a finite subset of $[0, 1]$. Each $h_A(x)$ contains the plausible membership degrees of x in A .

For example, $h_A(x) = \{0.55, 0.65, 0.70\}$ means that the available assessments of membership are 0.55, 0.65, and 0.70. These values should not be interpreted as membership, non-membership, and hesitation. They are alternative possible membership degrees.

3.2 Score and spread

For a non-empty hesitant membership set h , a simple score can be defined as $s(h) = (1/|h|) \sum \gamma$, for $\gamma \in h$. Its spread may be described by $\max(h) - \min(h)$. The score summarises central tendency, while the spread records disagreement or hesitation among the represented values. Other score functions may be selected, but the chosen function must be stated and applied consistently.

4. Application I: Human Reliability Analysis using HFS

4.1 Problem description

Consider an operator who must press the correct stop button after a warning alarm. The outcome can be affected by experience, fatigue, stress, workload, training, and the operating environment. In practice, experts may disagree about the degree to which a factor increases error risk. HFS can retain a set of plausible assessments for each factor.

4.2 Performance-shaping factors

Factor	Meaning in the HRA model	Illustrative assessment source
Experience / training	Higher experience and training may reduce error likelihood	Expert rating, training records
Fatigue	Greater fatigue may increase error likelihood	Shift duration, expert rating

Stress	High stress may impair performance	Operational assessment
Workload	Excessive workload may increase slips or omissions	Task analysis and expert rating

The directions above are modelling assumptions that must be checked for the task under study. A factor such as experience should not be treated as an error-increasing factor merely because its raw membership score is high; the meaning and polarity of every factor must be defined before aggregation.

4.3 HFS linguistic scale

The following is a proposed elicitation template, not data extracted from the original PDF. Multiple values in each set represent plausible assessments supplied by different experts or elicitation rounds.

Linguistic term	Example hesitant membership set h	Mean score
Low	{0.20, 0.30, 0.35}	0.283
Medium	{0.45, 0.50, 0.60}	0.517
High	{0.70, 0.80, 0.85}	0.783

These numbers are illustrative only. A real study must collect expert ratings, define whether membership refers to the presence of a risk factor or its contribution to error, and document how disagreement is converted into a hesitant set.

4.4 Proposed HFS-based HRA procedure

To Define the task and the error event precisely (for example, failure to press the correct stop button within the allowed time).

To Select performance-shaping factors relevant to the task and define the direction of risk for each factor.



To Collect ratings from multiple experts or repeated assessments. Encode the plausible membership degrees for each factor as a hesitant set.

To Specify factor weights w_i and justify them using expert consensus, a validated weighting method, or operational evidence.

To Calculate a factor score s_i using a stated score function, or use a fully specified HFS aggregation operator.

To Combine factor scores while preserving the risk direction of each factor. For protective factors such as experience, reverse or otherwise model the scale consistently.

To Map the aggregate risk score to HEP using a calibrated mapping based on observed data or a justified HRA calibration procedure.

To Perform sensitivity analysis and compare estimates against available incident data or established HRA methods.

4.5 Formula specification

Let h_i be the hesitant membership set for factor i and $s_i = (1/|h_i|) \sum \gamma$ for $\gamma \in h_i$. Let w_i be the weight of factor i , with $\sum w_i = 1$. The aggregate factor score is:

$$S = \sum_i w_i s_i$$

This aggregate score is not itself a probability. To estimate human error probability, a calibration function g must be defined from relevant data or an established mapping:

$$\text{HEP} = g(S, \text{task context, factor directions}), \quad 0 \leq \text{HEP} \leq 1$$

The original PDF uses $\text{HEP} = 1 - \text{Score}$ after defining $\text{Score} = \text{Yes} - \text{No}$. That formula belongs to the paper's IFS-style example and must not be carried over unchanged to HFS, because an HFS does not inherently provide separate yes and no values. A calibrated HFS-to-HEP mapping is required.

4.6 Illustrative calculation template (not an empirical result)

Suppose a study has selected two factors and assigned weights $w_1 = 0.6$ and $w_2 = 0.4$. Suppose the elicited hesitant sets are $h_1 = \{0.70, 0.80\}$ and $h_2 = \{0.40, 0.60\}$. Their mean scores are $s_1 = 0.75$ and $s_2 = 0.50$. The



weighted score is $S = 0.6(0.75) + 0.4(0.50) = 0.65$. This value is only an aggregate score. It cannot be called HEP unless a validated calibration function g is specified.

Factor	Weight	Illustrative hesitant set	Mean score	Weighted score
Factor 1	0.6	{0.70, 0.80}	0.75	0.45
Factor 2	0.4	{0.40, 0.60}	0.50	0.20
Total	1.0	—	—	$S = 0.65$

This numerical example demonstrates arithmetic only. It is not a result from the source paper, not validated operator data, and not a measured human error probability.

4.7 HRA validation plan

- Compare HFS estimates with available incident/error data or a defensible reference HRA method.
- Report calibration method, sample size, expert-selection process, and uncertainty.
- Test how estimates change when experts, factor weights, or hesitant membership values change.
- Report MAE or Brier score only when observed outcome labels and a valid evaluation design are available.
- Avoid claiming that HFS is more accurate until a controlled comparison supports the claim.

5. Application II: HFS-based NIFTY stock-market time-series forecasting

5.1 Source data retained from the supplied PDF

The source paper provides eleven NIFTY closing values. These observations are reproduced below as source-derived data. They are a small illustrative sequence and should not be treated as sufficient evidence of general forecasting performance.

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

5.2 Universe of discourse and intervals

The source paper uses minimum 23,650, maximum 24,400, universe $U = [23,600, 24,500)$, and interval length 100. The following interval partition is retained as a starting point. Boundary conventions must be applied consistently in implementation.

Interval	Range	Midpoint
I1	[23600, 23700)	23650
I2	[23700, 23800)	23750
I3	[23800, 23900)	23850
I4	[23900, 24000)	23950
I5	[24000, 24100)	24050

I6	[24100, 24200)	24150
I7	[24200, 24300)	24250
I8	[24300, 24400)	24350
I9	[24400, 24500)	24450

5.3 Define multiple membership functions:

We construct an HFS, we will use three triangular membership functions with different widths. For each interval I_j , let its midpoint be C_j . Define three triangles:

Narrow triangle: C_j-50, C_j, C_j+50

Medium triangle: C_j-100, C_j, C_j+100

Wide triangle: C_j-150, C_j, C_j+150

HFS representation for price observations

An HFS forecasting model needs a clear rule for creating more than one membership value. The source paper uses a single triangular membership value and defines non-membership as $1 - \mu$, leaving zero hesitation. That construction is not an HFS model. For an HFS conversion, this draft proposes obtaining multiple membership values from (i) a set of predeclared triangular membership functions with different widths, (ii) multiple expert assessments, or (iii) multiple calibrated membership estimators. The chosen source of hesitation must be justified and fixed before evaluating the test data.

5.4 Proposed HFS fuzzification

This subsection gives a reproducible numerical illustration of how the eleven NIFTY closing observations in this paper can be represented using hesitant fuzzy membership sets. The interval partition is retained from Section 5.2. The three membership-function widths introduced below are proposed modelling choices for illustration and are not empirical parameters reported by the source paper.

Step 1: Assign each observed closing price to an interval. The universe is $U = [23600, 24500)$, partitioned into nine half-open intervals of length 100. A value exactly on a boundary is assigned to the interval whose left endpoint equals that value; thus 24400 belongs to $I_9 = [24400, 24500)$.

Interval	Price range	Midpoint
I1	[23600, 23700)	23650
I2	[23700, 23800)	23750
I3	[23800, 23900)	23850
I4	[23900, 24000)	23950
I5	[24000, 24100)	24050
I6	[24100, 24200)	24150
I7	[24200, 24300)	24250
I8	[24300, 24400)	24350
I9	[24400, 24500)	24450

Step 2: Specify three triangular membership functions in advance. For interval I_j with midpoint C_j , define a narrow triangle with parameters (C_j-50, C_j, C_j+50) , a medium triangle (C_j-100, C_j, C_j+100) , and a wide triangle (C_j-150, C_j, C_j+150) . The same widths are applied to every interval, and the parameters must not be tuned using test-period forecast errors.

For any triangle with parameters (a,b,c) , its membership function is:

$\mu(x; a,b,c) = 0$, if $x \leq a$ or $x \geq c$; $(x - a)/(b - a)$, if $a < x \leq b$; and $(c - x)/(c - b)$, if $b < x < c$. At the centre b , $\mu(b) = 1$.

Step 3: Collect the three membership estimates into an HFS. For an observation x and interval I_j , where N , M and W denote the narrow, medium and wide triangles. These are alternative membership degrees,

The parameters are $a=23700$, $b=23750$, and $c=23800$.

consider $x = 23780$. It lies in $I_2 = [23700, 23800)$, whose midpoint is $c = 23750$.

Narrow membership function: $\mu_1^{(n)}(23780) = (23800 - 23780)/(23800-23750) = 0.40$

Medium membership function: $\mu_2^{(m)}(23780) = (23850 - 23780)/(23850-23750) = 0.70$.

Wide membership function: $\mu_2^{(w)}(23780) = (23900 - 23780)/(23900 - 23750) = 0.80$.

Therefore hesitant membership set $h_2(23780) = \{0.40, 0.70, 0.80\}$.

Its mean score is $s(h_2) = (0.40 + 0.70 + 0.80)/3 = 0.6333$,

Step 4: Using the same three triangular functions, the membership values for the corresponding interval states are calculated as follows.

T	NIFTY close x_t	Assigned interval	HFS $h_j(x_t) = \{\text{narrow, medium, wide}\}$	Mean score
1	23650	I1	$\{1.0000, 1.0000, 1.0000\}$	1.0000
2	23780	I2	$\{0.4000, 0.7000, 0.8000\}$	0.6333
3	23820	I3	$\{0.4000, 0.7000, 0.8000\}$	0.6333
4	23910	I4	$\{0.2000, 0.6000, 0.7333\}$	0.5111
5	24050	I5	$\{1.0000, 1.0000, 1.0000\}$	1.0000
6	23980	I4	$\{0.4000, 0.7000, 0.8000\}$	0.6333
7	24010	I5	$\{0.2000, 0.6000, 0.7333\}$	0.5111
8	24150	I6	$\{1.0000, 1.0000, 1.0000\}$	1.0000
9	24280	I7	$\{0.4000, 0.7000, 0.8000\}$	0.6333

			0.8000}	
10	24320	I8	{0.4000, 0.7000, 0.8000}	0.6333
11	24400	I9	{0.0000, 0.5000, 0.6667}	0.3889

For the last observation, $x = 24400$ is exactly the left boundary of I9. Its distance from midpoint 24450 is 50, so the narrow membership is 0, the medium membership is 0.50, and the wide membership is $2/3 \approx 0.6667$. The narrow triangle gives zero because 24400 is exactly its left endpoint. The medium and wide triangles still give positive membership values.

Step 5: Decide how interval labels are selected for forecasting. The table above reports the HFS associated with the interval containing each observation; it does not, by itself, define all fuzzy logical relationships. One simple, deterministic option is to compute a mean score for every interval whose membership functions have non-zero support and select the interval with the largest score. A tie-breaking rule must be declared before modelling. Alternatively, retain multiple interval labels and define an explicit HFS rule-combination operator. The selected option must be used consistently when constructing first- or second-order fuzzy logical relationship groups.

5.5 HFS fuzzy logical relationships and forecasting:

This section develops the next stage of your Hesitant Fuzzy Set (HFS)-based NIFTY stock-market forecasting model. It explains how to convert the fuzzified NIFTY observations into fuzzy states, construct second-order fuzzy logical relationships (FLRs), group the relationships into FLRGs, and calculate numerical forecasts.

5.5.1 Selection of fuzzy states: After completing HFS fuzzification in Section 5.4, each observation has a hesitant membership set. To construct a second-order forecasting model, we need a consistent rule for selecting a state for each observation.

Let the hesitant membership set associated with observation x_t and interval I_j be

$h_j(x_t) = \{\gamma_{j1}, \gamma_{j2}, \dots, \gamma_{jK}\}$. Use the mean score $s_j(x_t) = (1/K) \sum \gamma_{jk}$.

The selected fuzzy state is: $A_t = \arg \max s_j(x_t)$ Here, A_t denotes the interval state assigned to the NIFTY observation at time t . If two intervals have the same highest score, use a predetermined tie-breaking rule,

such as choosing the interval whose midpoint is closest to the observed price. The following worked example uses the assigned-interval HFS values from Section 5.4 and the interval labels shown in the source data in table:

Time t	NIFTY	Selected state
1	23650	A_1
2	23780	A_2
3	23820	A_3
4	23910	A_4
5	24050	A_5
6	23980	A_4
7	24010	A_5
8	24150	A_6
9	24280	A_7
10	24320	A_8
11	24400	A_9

These states provide the input for constructing the fuzzy logical relationships.

5.5.2 Constructing second-order fuzzy logical relationships

A second-order fuzzy logical relationship (FLR) uses the two previous states to predict the current state. Its general form is $(A_{t-2}, A_{t-1} \rightarrow A_t)$. For example, if the states at times 1 and 2 are A_1 and A_2 and the state at time 3 is A_3 , the rule is $(A_1, A_2) \rightarrow A_3$. Apply this construction successively to the complete training sequence. Only observations available in the training period may be used to build the rule base; test-period outcomes must not be used to create or adjust rules.

For the 11-observation illustration, the second-order relationships are:

Target time t	Antecedent (A_{t-2}, A_{t-1})	Consequent A_t	FLR
3	(A_1, A_2)	A_3	$(A_1, A_2) \rightarrow A_3$
4	(A_2, A_3)	A_4	$(A_2, A_3) \rightarrow A_4$
5	(A_3, A_4)	A_5	$(A_3, A_4) \rightarrow A_5$
6	(A_4, A_5)	A_4	$(A_4, A_5) \rightarrow A_4$
7	(A_5, A_4)	A_5	$(A_5, A_4) \rightarrow A_5$
8	(A_4, A_5)	A_6	$(A_4, A_5) \rightarrow A_6$
9	(A_5, A_6)	A_7	$(A_5, A_6) \rightarrow A_7$
10	(A_6, A_7)	A_8	$(A_6, A_7) \rightarrow A_8$
11	(A_7, A_8)	A_9	$(A_7, A_8) \rightarrow A_9$

5.5.3 Forming fuzzy logical relationship groups (FLRGs)

Rules with identical antecedents are grouped together. In this example, the antecedent (A_4, A_5) occurs twice and has two consequents, A_4 and A_6 . Its FLRG is therefore $(A_4, A_5) \rightarrow \{A_4, A_6\}$. All other antecedents in this small sequence occur once. Grouping repeated antecedents avoids treating the same historical condition as two unrelated rules.

Antecedent pair	Consequent state(s)	Frequency
(A_1, A_2)	A_3	1
(A_2, A_3)	A_4	1
(A_3, A_4)	A_5	1
(A_4, A_5)	A_4, A_6	2
(A_5, A_4)	A_5	1

(A_5, A_6)	A_7	1
(A_6, A_7)	A_8	1
(A_7, A_8)	A_9	1

5.5.4 Defuzzification and crisp forecast

After constructing the FLRGs, the model must convert the predicted fuzzy states into a numerical NIFTY closing-price forecast. For the nine intervals, the midpoints are:

Number	Mid point
1	23650
2	23750
3	23850
4	23950
5	24050
6	24150
7	24250
8	24350
9	24450

For a rule with multiple consequents, a weighted average can be used: $\text{Forecast}(x_t) = [\sum_j q_j m_j] / [\sum_j q_j]$, where m_j is the midpoint of consequent interval j and $q_j \geq 0$. The denominator must be positive. For the FLRG $(A_4, A_5) \rightarrow \{A_4, A_6\}$, equal weights give $\text{Forecast} = (23950 + 24150)/2 = 24050$. This value is the forecast produced by that rule group under the stated equal-weight convention.

5.5.5 Worked illustration of rule-based forecasts

Applying the midpoint method to the available relationships gives the following illustrative results.

T	Antecedent	Consequent(s)	Illustrative forecast	Observed NIFTY
3	(A_1, A_2)	A_3	23850	23820
4	(A_2, A_3)	A_4	23950	23910
5	(A_3, A_4)	A_5	24050	24050
6	(A_4, A_5)	A_4, A_6	24050	23980
7	(A_5, A_4)	A_5	24050	24010
8	(A_4, A_5)	A_4, A_6	24050	24150
9	(A_5, A_6)	A_7	24250	24280
10	(A_6, A_7)	A_8	24350	24320
11	(A_7, A_8)	A_9	24450	24400

5.6 Forecast accuracy measures

Forecast accuracy measures are used to evaluate how closely the predicted stock-market values match the actual observed values. In this research, these measures are used to evaluate the proposed Hesitant Fuzzy Set-Based Explainable AI Model for Stock Market Forecasting.

The model uses historical NIFTY closing prices, hesitant fuzzy membership values, fuzzy logical relationships (FLRs), and a forecasting rule base to generate predictions. The accuracy of the resulting forecasts must be evaluated by comparing predicted closing prices with the corresponding actual closing prices.

A forecasting model is considered more accurate when its prediction errors are smaller. However, accuracy should be assessed using several measures because each measure highlights a different aspect of the forecasting error.

5.6.1 Actual and Forecast value

The following table illustrates how forecast errors are calculated.

Time	Actual closing price (A_t)	Forecast (A_t) ⁻	Error (e_t)	Absolute error
1	23780	23750	30	30
2	23820	23850	-30	30
3	23910	23950	-40	40
4	24050	24000	50	50

These values are an illustrative example, not validated forecasts from the proposed HFS model.

Metric	Formula	Interpretation
MAE	$MAE = (1/n) \sum y_t - \hat{y}_t $	Average absolute forecast error
MSE	$MSE = (1/n) \sum (y_t - \hat{y}_t)^2$	Penalises larger errors
RMSE	$RMSE = \sqrt{MSE}$	Error in the original data units
MAPE	$MAPE = (100/n) \sum (y_t - \hat{y}_t)/y_t $	Average absolute percentage error

Use the same forecast dates and metric conventions for every competing model. For a stock index that is always positive, MAPE can be computed, but a very small MAPE from only a few observations should not be interpreted as proof of reliable future performance.

5.7 Source results versus HFS results

The supplied PDF reports $MAE = 43.33$, $MSE = 2588.89$, $RMSE = 50.88$, and $MAPE = 0.18\%$ for its second-order intuitionistic fuzzy time-series procedure. These are source-paper figures, not HFS results. They must be recalculated after defining the hesitant membership functions, fuzzification rule, HFS score/aggregation, rule groups, forecast values, and test protocol.

Item	Value in supplied PDF	Status after HFS conversion
NIFTY observations	11 values, 23,650 to 24,400	Retained as source data; verify against official market data before publication
Universe	[23,600, 24,500)	Retained as a starting partition
Interval length	100	Retained; test alternative partitions in sensitivity analysis
Model order	Second order	Can be retained, but rules must be rebuilt from HFS states
MAE	43.33	Recalculate from new HFS forecasts

MSE	2588.89	Recalculate from new HFS forecasts
RMSE	50.88	Recalculate from new HFS forecasts
MAPE	0.18%	Recalculate and verify denominator, forecast set, and rounding

6. Conclusion and future work

The proposed HFS-based framework provides a systematic approach to representing uncertainty in stock-market forecasting and human reliability analysis. Its use of hesitant membership values and fuzzy logical relationships offers opportunities for modelling ambiguous information and developing interpretable analytical procedures. Future improvements may include optimized membership functions, adaptive forecasting rules, integration with AI, more comprehensive validation, and practical software implementation. The most important next step is to validate the proposed methodology using larger datasets, clearly defined experimental procedures, and appropriate benchmark comparisons. Once these investigations have been completed, the framework can be assessed more reliably in terms of predictive accuracy, robustness, interpretability, and practical usefulness.

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