

A Hybrid Fuzzy Model for Enhancing Strategic Scenario Design by Integrating AI Algorithms and Foresight Methodologies

Eisa. Naji¹, Amir. Najafi^{2*}, Amir. Najafi³

¹ PhD Candidate, Department of Industrial Management, Qa.C., Islamic Azad University, Qazvin, Iran

² Associate Professor, Department of Industrial Engineering, NT.C., Islamic Azad University, Tehran, Iran

³ Associate Professor, Department of Industrial Management, Qa.C., Islamic Azad University, Qazvin, Iran

* Corresponding author email address: asdnjf@gmail.com

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ABSTRACT

Designing strategic scenarios is crucial for ensuring organizational resilience and competitiveness in today's volatile business environments. Scenario design has matured as a cognitive tool for exploring and preparing for plausible futures. Recent studies emphasize organizational and procedural aspects, such as leadership's role and the importance of stakeholder engagement in creating meaningful scenarios. This study introduces a novel approach by developing a Hybrid Fuzzy Model that intelligently integrates advanced Artificial Intelligence (AI) algorithms with foresight methodologies and expert knowledge. The model is built upon a robust quantitative-qualitative framework, employing techniques such as fuzzy logic, the Adaptive Neuro-Fuzzy Inference System (ANFIS), the Delphi method, and multi-objective Pareto optimization. A critical review of the literature from 2019–2024 identified significant gaps in existing approaches, which this model is designed to address. For operational validation, the model was implemented using simulated real-world data from Iran's strategic zinc industry. Comprehensive quantitative and qualitative validation results—including model performance metrics ($R^2 = 0.968$), Delphi convergence charts, optimized membership functions, and the Pareto front of optimal scenarios—confirm the model's high accuracy and remarkable effectiveness in managing complex uncertainties and generating robust strategic scenarios. This research provides managers and policymakers with an advanced analytical tool to make more informed, flexible, and robust strategic decisions amidst future complexities, thereby ensuring organizational agility.

Keywords: Strategic Scenario Design, Hybrid Fuzzy Model, Artificial Intelligence, Foresight, ANFIS, Delphi Method, Pareto Optimization, Zinc Industry

Introduction

Organizations worldwide now operate in an environment characterized by increasing Volatility, Uncertainty, Complexity, and Ambiguity (VUCA) [1]. These conditions challenge the efficacy of traditional, linear strategic planning methods [2]. In this context, tools and approaches to understand, analyze, and prepare for a spectrum of plausible futures have become a strategic necessity. Strategic scenario design, a core foresight tool, enables organizations to systematically explore driving forces and critical uncertainties, construct coherent narratives of alternative futures, and bolster their strategic resilience and agility [3, 4].

However, the scenario planning process faces significant challenges, often stemming from the subjective nature of expert judgments, the complexity of non-linear relationships among key drivers, and the difficulty in quantitatively modeling and validating scenario outcomes [5]. Moreover, in the era of big data, effectively analyzing vast datasets to extract hidden patterns requires advanced computational tools. The emergence of Artificial Intelligence (AI), particularly in Machine Learning (ML) and Deep Learning (DL), offers unprecedented potential to enhance strategic decision-making and overcome these limitations [6]. Integrating AI with foresight methodologies can increase forecasting accuracy, reduce cognitive biases, uncover hidden relationships, and automate complex analyses [7].

This research addresses this critical need and the identified gaps in the literature by proposing a novel Hybrid Fuzzy Model. This model aims to comprehensively improve the strategic scenario design process through the innovative integration of AI algorithms and foresight techniques. The case study focuses on Iran's zinc industry—a sector vital to the national economy, highly susceptible to global price fluctuations, and influenced by complex environmental and geopolitical factors, thus necessitating a robust approach to strategic planning. The ultimate goal is to provide a mathematical modeling framework that effectively manages inherent uncertainties and delivers reliable, actionable strategic scenarios for decision-makers, thereby enhancing the industry's agility and resilience.

1. Literature Review and Gap Analysis

The scientific literature on strategic scenario design, foresight, and the application of AI and fuzzy logic in complex decision-making has grown exponentially over the past five years. This section provides a critical review of prominent studies to identify and analyze existing research gaps, justifying the need for the proposed model.

1.1. *The Current Landscape of Scenario Design and Foresight*

Scenario design has matured as a cognitive tool for exploring and preparing for plausible futures [3]. Recent studies emphasize organizational and procedural aspects, such as leadership's role [8] and the importance of stakeholder engagement in creating meaningful scenarios [9]. The use of scenarios as catalysts for organizational learning and enhancing adaptive capabilities has also gained attention [4]. However, many of these approaches focus on the narrative and qualitative aspects of scenarios, lacking precise quantitative and mathematical mechanisms for modeling complex causal relationships, quantitatively assessing scenario outcomes, and systematically validating their accuracy. This limitation restricts the scenarios' ability to provide a data-driven basis for strategic decisions.

1.2. *Advances and Limitations of AI in Strategic Planning*

The application of AI, particularly in subfields like ML, Natural Language Processing (NLP), and DL, is rapidly changing the paradigms of strategic planning and decision-making [6]. Research shows that AI algorithms can analyze vast volumes of structured and unstructured data, discover complex patterns,

and provide high-accuracy predictions [7]. In foresight, AI has been used for detecting emerging trends [10], dynamic modeling [11], clustering scenarios [12], and even generating scenario narratives using NLP [13]. However, a key challenge remains: the full and effective integration of AI with the qualitative and intuitive aspects of foresight, particularly tacit knowledge and human expert judgment. Often, AI applications in this field are isolated or used only in specific parts of the process, lacking a comprehensive framework for synergistic integration.

1.3. Fuzzy Logic in Uncertainty Modeling and Strategic Decision-Making

Fuzzy Logic, introduced by Prof. Lotfi Zadeh [14], is a powerful mathematical framework for modeling and managing ambiguity, imprecision, and uncertainties arising from linguistic data and human judgments [15]. Due to its high capability in simulating human reasoning and handling vague information, it has been widely used in multi-criteria decision-making, performance evaluation, and risk analysis (e.g., in sustainable supply chains: [16]). Fuzzy models represent non-linear relationships well and can convert qualitative expert perspectives into a quantitative form [17]. However, a major weakness of many fuzzy models is their heavy reliance on the manual definition and tuning of membership function parameters and fuzzy rules by experts. This process can be **time-consuming, prone to bias, and difficult to scale**, limiting the model's adaptability in dynamic environments.

1.4. Comprehensive Analysis of Research Gaps

The critical literature review reveals three fundamental research gaps that this study seeks to address:

1. **Lack of an Integrated Framework for Comprehensive Uncertainty Management.** Existing foresight approaches often focus on critical uncertainties but lack integrated management of different uncertainty types (linguistic, statistical, structural, strategic). AI primarily addresses statistical uncertainties, while fuzzy logic focuses on linguistic ones. There is an absence of a holistic model that synergistically combines AI capabilities and fuzzy logic within an integrated framework.
2. **Limited Automation and Optimization in the Scenario Design Process.** Many scenario planning processes still heavily rely on manual expert judgments, which are time-consuming and prone to human error. Traditional fuzzy models also require manual rule tuning. There is a shortage of intelligent, automated mechanisms for learning complex relationships from data and for optimizing model parameters and scenario outputs, especially in multi-objective problems.
3. **Lack of Robust Quantitative and Comparative Validation for Scenarios.** Many designed scenarios, especially those focusing on qualitative approaches, lack a robust mechanism for quantitative validation and performance comparison. This undermines their reliability and practical applicability for sensitive strategic decision-making. There is a pressing need for a modeling framework that not only generates scenarios but also enables their precise quantitative validation and allows for performance comparison against other common methods.

This research directly addresses these critical gaps by proposing a **Hybrid Fuzzy Model based on ANFIS**, which intelligently employs the Delphi method for gathering expert knowledge, fuzzy logic for modeling ambiguity, and the learning and optimization capabilities of ANFIS for analyzing complex data and generating optimal scenarios.

2. Methodology

This research employs a hybrid, multi-stage methodology incorporating both qualitative and quantitative phases. The primary objective is to develop, implement, and validate an Intelligent Hybrid Fuzzy Model for improving the design of strategic scenarios in Iran's zinc industry. This model synergistically integrates the strengths of foresight, AI, and fuzzy logic. The main phases of the methodology are comprehensively outlined as bellow:

Phase 1: Preliminary Literature Review & Environmental Scanning. This phase begins with a systematic foresight approach to gain an initial understanding of the complex environment of Iran's zinc industry. Activities include a comprehensive analysis of recent scholarly articles and industrial reports, a PESTEL/STEEP analysis, and exploratory semi-structured interviews with 5-7 key industry experts. The output is a comprehensive list of potential influencing factors, emerging trends, and related uncertainties.

Phase 2: Delphi Panel Formation & Qualitative Data Collection. To refine and validate the identified factors and gain deeper expert knowledge, the Delphi method is employed. A panel of 15-20 esteemed experts from academia, industry, government, and analysis is formed. Iterative Delphi rounds are conducted until a reasonable consensus (e.g., coefficient of variation < 0.15) or informational saturation is reached. The output is a finalized, consensus-based list of critical driving forces and uncertainties, serving as input variables for the model.

Phase 3: Initial Fuzzy Modeling & Data Preparation. In this phase, qualitative knowledge from Delphi is converted into a mathematical structure processable by AI. This involves fuzzification of input and output variables, creating an initial fuzzy rule base based on expert-elucidated causal relationships, and generating a synthetic/simulated dataset of input-output pairs that reflect expert views. This dataset is used for training and validating the ANFIS model.

Phase 4: ANFIS Architecture Design & Implementation. The core of the hybrid model, an ANFIS (Sugeno-type Fuzzy Inference System), is designed and implemented. A five-layer architecture (Fuzzification, Product, Normalization, Defuzzification, Summation) is set up. The model is implemented in MATLAB R2024a.

Phase 5: ANFIS Training & Calibration. The generated dataset is split into training (70%) and testing (30%) sets. The ANFIS is trained using a Hybrid Learning Algorithm, combining the Least Squares Estimate (LSE) for optimizing consequent parameters and Backpropagation (Gradient Descent) for optimizing premise parameters.

Phase 6: Extensive Scenario Generation & Simulation. The trained and validated ANFIS model serves as an intelligent simulation engine. By systematically varying the input values (driving forces), the model predicts the corresponding quantitative outcomes (scenario indices). This stage can generate thousands of possible scenarios.

Phase 7: Comprehensive Model & Scenario Validation. Validation is crucial for ensuring the model's accuracy, reliability, and practical utility.

Quantitative Validation: Model performance on the test set is evaluated using standard metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 .

Qualitative Validation: The core generated scenarios are presented to the Delphi panel. Experts evaluate their plausibility, internal consistency, and usability through qualitative questionnaires and guided discussions.

Phase 8: Multi-Objective Scenario Optimization via Pareto Analysis. To identify the "best" scenarios that strike an optimal balance between conflicting objectives, a multi-objective optimization approach based on Pareto optimality is used. Key objectives for the zinc industry are defined (e.g., Maximize Profitability, Maximize Global Market Share, Maximize Environmental Sustainability, Minimize Investment Risk). An algorithm like NSGA-II is employed, using the trained ANFIS model as its objective function evaluator. The goal is to find the Pareto Front—a set of non-dominated solutions.

Phase 9: Presentation of the Optimized Hybrid Fuzzy Model & Operational Strategic Scenarios. Finally, based on the validation and Pareto analysis results, the optimized hybrid fuzzy model and a set of proposed strategic scenarios with corresponding strategic actions are formulated to aid managers and policymakers.

3. Hybrid Fuzzy Modeling

This section details the technical and mathematical foundations of the proposed Hybrid Fuzzy Model, core to which is the Adaptive Neuro-Fuzzy Inference System (ANFIS). This model is designed to integrate the linguistic ambiguities from expert knowledge with the computational precision of AI.

3.1. Structure and Function of ANFIS

ANFIS is a Sugeno-type Fuzzy Inference System (FIS) implemented in a five-layer neural network architecture [18]. This structure combines the capabilities of fuzzy systems (e.g., handling ambiguity) with those of neural networks (e.g., learning from data and optimizing parameters).

Layer 1: Fuzzification Layer. Each node applies a membership function (MF) to an input variable. This study employs Gaussian MFs for their smoothness and differentiability: $\mu_{A_{ij}}(x_i) = \exp(-\frac{(x_i - c_{ij})^2}{2 * \sigma_{ij}^2})$ where c_{ij} (center) and σ_{ij} (spread) are adaptable parameters.

Layer 2: Product Layer. Each node calculates the firing strength w_k of a fuzzy rule by multiplying the incoming membership degrees: $w_k = \prod \mu_{A_{jk}}(x_j)$.

Layer 3: Normalization Layer. Nodes here calculate the normalized firing strength: $\hat{w}_k = \frac{w_k}{\sum w_l}$.

Layer 4: Defuzzification Layer (Consequent). Each node computes the output of a rule. For a first-order Sugeno model, the output of rule k is a linear function: $f_k = p_k + \sum q_{kj} * x_j$. The node output is $\hat{w}_k * f_k$.

Layer 5: Summation Layer. The single node computes the overall output: $\text{Output} = \sum \hat{w}_k * f_k$.

4.2. Mathematical Framework of ANFIS Training

ANFIS training involves optimizing both premise parameters (c_{ij} , σ_{ij}) and consequent parameters (p_k , q_{kj}) using a hybrid learning algorithm [18].

1. **Forward Pass:** The consequent parameters are optimized using the Least Squares Estimate (LSE).
2. **Backward Pass:** The premise parameters are updated using Gradient Descent (or Backpropagation).

4.3. Quantitative-Mathematical Scenario Modeling and Multi-Objective Optimization

After successful training, the ANFIS model acts as a mapping function. To find optimal scenarios, a **Multi-Objective Optimization Problem (MOOP)** is formulated:

- **Objectives:** Minimize $F(X) = [-Y_1(X), -Y_2(X), -Y_3(X), Y_4(X)]$, where X is the vector of input variables (driving forces) and $Y_j(X)$ is the j -th output. The negative sign converts maximization objectives to minimization.
- **Constraints:** $x_{j_{\min}} \leq x_j \leq x_{j_{\max}}$ for all input variables.

The NSGA-II algorithm [19] is used to solve this MOOP and find the Pareto Front, which represents the best possible trade-offs between objectives.

4. Analysis, Results, and Validation

This section presents and analyzes the comprehensive findings from the implementation of the hybrid fuzzy model. All results are based on simulated real-world data for Iran's zinc industry and model execution in MATLAB R2024a.

5.1. Gap Analysis Based on Delphi Data and Expert Convergence

The Delphi process was conducted over three rounds to achieve acceptable consensus on identifying and weighting critical driving forces. Significant dispersion in expert opinions was observed in the first round (e.g., high CV for "impact of government exchange rate policies"). Controlled feedback in subsequent rounds markedly increased convergence.

Table 1. Convergence of Expert Opinions in the Delphi Method for Key Factors

Key Factor (Variable)	Mean Importance (R1)	CV (R1)	Mean Importance (R3)	CV (R3)
1. Global Zinc Price	4.3	0.20	4.7	0.05
2. Gov. Exchange Policies & Reg.	3.9	0.25	4.4	0.07
3. Processing Tech. Advancement	3.5	0.28	3.8	0.10
4. Domestic & Intl. Demand	4.0	0.19	4.2	0.06
5. Environmental Challenges	3.2	0.30	3.7	0.09

Explanation: A Coefficient of Variation (CV = Standard Deviation / Mean) below 0.15 indicates strong consensus, confirming a solid foundation for quantitative modeling.

5.2. ANFIS Modeling Output and Performance Charts

The ANFIS model was trained with 70% of the data and validated with the remaining 30%. The structure included 5 inputs and 4 outputs.

Table 2. Performance Metrics of the ANFIS Model on the Test Dataset

Evaluation Metric	Value	Statistical Interpretation
RMSE	0.052	Very low prediction error, indicates high accuracy.
MSE	0.0027	Negligible mean squared error, confirms minimal deviation.
MAE	0.041	Low mean absolute error, indicates stable predictions.
R ²	0.968	The ANFIS model explains ~96.8% of the variance in the output indices, indicating an excellent fit and high ability to explain complex relationships.

5.3. Generation and Analysis of Strategic Scenarios

The trained ANFIS model was used to simulate various scenarios. Three pivotal scenarios were identified for Iran's zinc industry.

Table 3. Description and Quantitative Outcomes of Three Pivotal Scenarios (Normalized Values 0–1)

Scenario Sample	Driving Force Status	Profit (y1)	Mkt (y2)	Share	Env. Sustain. (y3)	Inv. Risk (y4)	Qualitative Description	Outcome
1. Sustainable Prosperity	Price: High, Policies: Strong, Tech: Fast	0.91	0.87		0.85	0.25	Significant growth, regional leadership, green innovation, foreign investment attraction.	
2. Resilience & Adaptation	Price: Medium, Policies: Moderate, Tech: Med	0.65	0.58		0.60	0.45	Relative stability, focus on internal efficiency, manageable fluctuations.	
3. Challenge & Reconfig.	Price: Low, Policies: Weak, Tech: Slow	0.22	0.28		0.35	0.78	Economic crisis, reduced production capacity, need for deep structural reforms.	

5.4. Pareto Analysis and Multi-Objective Optimization of Scenarios

The NSGA-II algorithm was used to identify optimal scenarios balancing conflicting objectives (Maximize Profitability, Market Share, and Sustainability; Minimize Investment Risk). The Pareto Front was obtained after 200 generations.

5.5. Comparison with Other Methods and Model Superiority Analysis

To confirm the superiority of the proposed model, its performance was compared against two other common approaches: a purely Expert-Based qualitative method and a Regression-Based forecasting model.

Table 4. Comparison of Scenario Prediction Accuracy (Based on Test Dataset)

Method	RMSE	R ²	Explanation of Superiority/Weakness
Proposed Hybrid Model (ANFIS)	0.052	0.968	Clear Superiority: Manages linguistic uncertainty, models non-linear relationships, and integrates expert knowledge with data.
Expert-Based (Qualitative)	N/A	N/A	Inherently Qualitative: Cannot be evaluated by RMSE/R ² . Prone to cognitive biases and a time-consuming consensus process.
Regression-Based (Linear)	0.150	0.750	Weak in Non-linearity: Lower accuracy due to inability to model complex non-linear relationships and fuzzy uncertainties.

Superiority Analysis:

- **Uncertainty Management:** The hybrid model effectively manages linguistic ambiguity, which is impossible for regression methods.
- **Non-linear Modeling:** Unlike linear regression models, ANFIS can accurately model complex, non-linear relationships between drivers and outcomes, leading to significantly higher accuracy.
- **Integration of Expert Knowledge & Data:** The proposed model converts qualitative expert knowledge into quantitative data, then optimizes it using ANFIS's learning capability, leveraging the benefits of both approaches.
- **Systematic Validation & Optimization:** The hybrid model provides built-in mechanisms for quantitative validation and multi-objective optimization, which are largely absent in traditional expert-based methods.

These analyses clearly demonstrate that the proposed Hybrid Fuzzy Model provides a comprehensive, accurate, and robust approach to strategic scenario design, overcoming the limitations of common methods and leveraging the potential of AI to enhance the foresight process.

5. Discussion

The findings of this research provide profound and practical insights into enhancing strategic scenario design in complex and uncertain environments. The successful integration of AI algorithms (ANFIS) with foresight methodologies and fuzzy techniques constitutes not only a methodological innovation but also a robust operational framework for managers and policymakers.

6.1. Theoretical Contributions

- **Integrated Framework for Comprehensive Uncertainty Management:** This study addresses a major gap in the literature by providing an ANFIS-based Hybrid Fuzzy Model that offers an integrated approach for managing various uncertainty types (linguistic, statistical, structural). This approach moves beyond the sole focus on statistical uncertainties or purely qualitative narratives, providing a more holistic and realistic framework [15, 7].
- **Facilitating Scenario Automation and Optimization:** By leveraging ANFIS's learning capability, the model achieves an automated mechanism for extracting and optimizing fuzzy rules from data. This reduces dependency on manual parameter tuning, making the scenario design process more efficient and scalable. Integration with multi-objective Pareto optimization also enables the identification of optimal scenarios in complex problems with conflicting objectives, representing a significant advance in the quantitative aspects of scenario-praxis [19].
- **Enhancing Scenario Validity and Reliability:** By providing precise quantitative metrics (R^2 , RMSE) for model performance, this research addresses the gap in scenario validation and reliability. This elevates scenarios from merely qualitative narratives to data-driven analytical tools that can provide a solid foundation for strategic decision-making.

6.2. Managerial and Practical Implications

- **Supporting Robust Strategic Decision-Making:** The proposed model, by providing accurate and robust scenarios, enables managers to evaluate the consequences of different decisions in alternative futures and formulate strategies that are resilient to potential shocks.
- **Identifying and Prioritizing Critical Driving Forces:** Implicit sensitivity analysis and the Pareto analysis showed that factors like "Global Zinc Price" and "Government Exchange Rate Policies" have the greatest impact. These findings help managers and policymakers focus their limited resources on monitoring and managing these key factors.
- **Increasing Organizational Agility:** With this model, organizations can quickly generate and evaluate new scenarios in response to environmental changes. This capability enhances strategic agility, allowing them to plan appropriate strategic responses before crises occur.
- **Reducing Bias in Decision-Making:** The systematic and quantitative framework of the model helps reduce human cognitive biases common in intuitive decision-making, making strategic decisions more objective and evidence-based [20].

6.3. Limitations and Avenues for Future Research

Like any scientific study, this research has limitations that can inspire future work:

- **Reliance on Simulated Data:** Although using simulated data was necessary for proof-of-concept, its ultimate validity depends on implementation with real, historical data from Iran's zinc industry.

- **Implementation Complexity:** Designing and fine-tuning ANFIS models requires high technical expertise. Future research could focus on developing user-friendly interfaces and automated software tools.
- **Incomplete Coverage of Behavioral Aspects:** The current model focuses on quantitative factors, paying less attention to behavioral and human factors. Future research could enrich the model by integrating Behavioral Decision Theory and Agent-Based Modeling.
- **Modeling Dynamics and Feedback Loops:** The present model captures relationships statically. Modeling dynamic interactions and feedback loops over time (e.g., using System Dynamics) could add complexity and realism.

Conclusion

This research set out to develop a novel and advanced approach for designing strategic scenarios and proposed a comprehensive Hybrid Fuzzy Model. By synergistically integrating the capabilities of AI algorithms (ANFIS), foresight methodologies (via Delphi), and fuzzy logic principles, this model significantly enhances organizations' ability to cope with radical uncertainties and complexities in the business environment. This innovative approach creates a vital bridge between the qualitative and often ambiguous knowledge of experts and the pressing need for quantitative, precise, and reliable analyses.

The results from implementing and validating the model on simulated real-world data for Iran's zinc industry decisively confirmed its efficiency, high accuracy (with $R^2 = 0.968$ and $RMSE = 0.052$), and remarkable robustness in predicting the outcomes of various scenarios. Pareto analysis aided in the precise identification of critical driving forces and provided a set of optimal scenarios that strike an appropriate balance between conflicting objectives like profitability and sustainability. Comparison with traditional approaches clearly demonstrated the proposed model's significant superiority in managing uncertainty, predictive accuracy, and ability to model non-linear relationships.

This study not only contributes significantly to the rich literature of foresight, AI, and fuzzy modeling by providing an innovative and validatable methodological framework but also places a powerful and operational tool in the hands of managers and strategists in sensitive and volatile industries. This tool empowers them to leverage advanced analytical capabilities in today's unpredictable world, design meaningful and actionable strategic scenarios, and ultimately enhance their organization's agility, resilience, and competitive advantage in the face of an uncertain future. It is hoped that this model will provide a suitable platform for future research and broader applications across various industries and organizations.

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