

Fuzzy Logic-Based Intelligent Systems for Uncertainty Handling

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ABSTRACT

Uncertainty is intrinsic to real-world intelligent systems, arising from imprecise sensor measurements, incomplete domain knowledge, vague linguistic descriptions, and stochastic environmental dynamics. Fuzzy logic — providing a formal calculus for graded truth values and linguistic variable manipulation — remains uniquely suited to modelling and propagating such uncertainty in a mathematically tractable and human-interpretable manner. This study presents FuzzyCore, a unified fuzzy logic-based intelligent systems framework integrating type-2 fuzzy sets for second-order uncertainty representation, a genetic algorithm-optimised fuzzy rule base, and a fuzzy cognitive map (FCM)-driven causal reasoning engine for complex multi-variable decision support. FuzzyCore was evaluated across four uncertainty-rich intelligent system applications: autonomous robot navigation under sensor noise (ROS2 TurtleBot4, Gaussian noise sigma = 0.15 m), medical diagnosis under incomplete symptom data (UCI Heart Disease dataset, 32.4% missing values), financial portfolio risk assessment under market volatility regime uncertainty (STOXX Europe 600, 2015–2025), and supply chain disruption risk scoring under geopolitical uncertainty (500 suppliers, 18 risk dimensions). FuzzyCore achieved navigation success rate of 94.3%, diagnosis AUC-ROC of 0.934, portfolio Sharpe ratio improvement of 0.38, and supply chain risk precision of 0.917 — surpassing crisp rule-based, probabilistic, and type-1 fuzzy baselines by 7.4–18.3%. Interpretability ratings from 36 domain experts averaged 4.5/5.0 — significantly exceeding neural network baselines (2.7/5.0). These results establish FuzzyCore as a robust, interpretable, and practically deployable framework for uncertainty handling across diverse intelligent system domains.

Keywords: fuzzy logic; uncertainty handling; type-2 fuzzy sets; fuzzy cognitive maps; intelligent systems; soft computing; interpretability; genetic algorithms

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1. Introduction

Real-world intelligent systems must routinely make decisions under multiple simultaneous forms of uncertainty: measurement noise from imperfect sensors, epistemic uncertainty from incomplete knowledge, linguistic imprecision in human-specified rules, and aleatory uncertainty from stochastic environment dynamics (Zadeh 1965; Dubois and Prade 1988). Probabilistic frameworks — Bayesian inference, Gaussian processes, Monte Carlo methods — provide principled uncertainty quantification for well-defined stochastic models but struggle with vague, linguistic, and non-probabilistic uncertainty. Fuzzy logic, introduced by Zadeh (1965) and extended to type-2 fuzzy sets by Mendel and John (2002), offers a complementary calculus that directly formalises graded membership, linguistic variables, and approximate reasoning — properties uniquely aligned with human expert knowledge representation and the imprecision inherent in natural language rule specification.

Despite extensive theoretical development, the practical integration of advanced fuzzy logic techniques — type-2 fuzzy sets, evolved rule bases, and causal reasoning maps — into unified intelligent systems frameworks deployable across heterogeneous real-world applications remains limited. Most deployed fuzzy systems use manually designed type-1 rule bases that fail to model uncertainty about the membership functions themselves, and lack principled mechanisms for multi-variable causal inference. This study presents FuzzyCore, addressing these limitations through an integrated framework validated

across four structurally distinct uncertainty-rich intelligent system applications.

2. Literature Review

2.1 Type-2 Fuzzy Sets and Evolved Rule Bases

Mendel and John (2002) formalised interval type-2 fuzzy sets, extending type-1 fuzzy logic to model uncertainty about membership function shape through a footprint of uncertainty (FOU). Type-2 FLS have demonstrated superior performance over type-1 in noisy classification (Castillo and Melin 2012) and control under measurement uncertainty (Hagras 2004). Genetic algorithms for fuzzy rule base optimisation (Cordón et al. 2001) simultaneously evolve rule structure and membership function parameters, achieving compact, accurate rule bases without expert hand-tuning. Cooperative coevolution of fuzzy rule subsets (Ishibuchi et al. 2007) scales to high-dimensional problems by decomposing the rule search space into manageable subproblems, enabling practical optimisation for real-world industrial and medical applications.

2.2 Fuzzy Cognitive Maps for Causal Reasoning

Fuzzy cognitive maps (FCMs), introduced by Kosko (1986), model causal relationships between domain concepts as a weighted directed graph with fuzzy edge weights, enabling qualitative dynamic simulation and scenario analysis without differential equation specification. FCMs have been applied to strategic planning (Papageorgiou et al. 2012), supply chain risk modelling (Koulouriotis et al. 2014), and clinical decision support (Papageorgiou 2011). Learning FCM weights from data

using evolutionary algorithms (Stach et al. 2005) enables data-driven causal model construction for domains where expert elicitation is impractical. Integration of type-2 FCMs with genetic rule base optimisation within a unified framework has not been previously demonstrated.

Table 1. Comparison of uncertainty handling methods for intelligent systems.

Method	Lingui stic UQ	Typ e-2	Evolv ed RB	Causal Inf.	Interpret ability
Bayesian Network	No	No	No	Yes	Moderate
Type-1 FLS (manual)	Yes	No	No	No	High
Type-1 FLS (evolved)	Yes	No	Yes	No	High
Type-2 FLS	Yes	Yes	No	No	Moderate
FCM	Yes	No	No	Yes	High
Neural Network	No	No	No	No	Low
FuzzyCore	Yes	Yes	Yes	Yes	High

UQ: Uncertainty Quantification; Type-2: Type-2 fuzzy set support;

Evolved RB: Evolved Rule Base; Causal Inf.: Causal Inference support.

3. Materials and Methods

3.1 FuzzyCore Architecture

FuzzyCore integrates three components. The Type-2 Fuzzy Inference Engine (T2FIE) implements interval type-2 Mamdani fuzzy inference with Gaussian primary membership functions

(mean μ , standard deviation σ) and uncertainty bounds $\pm \Delta\sigma$ parameterising the FOU. Centroid type reduction (Karnik-Mendel algorithm) converts type-2 outputs to crisp values. The Genetic Rule Base Optimiser (GRBO) uses a steady-state GA (population 200, tournament selection, BLX-alpha crossover $\alpha = 0.3$, mutation rate 0.02) to jointly optimise rule structure (antecedent-consequent pairs), membership function parameters, and FOU widths, minimising a combined accuracy + rule complexity objective (Pareto front selection, 100 generations). The FCM Causal Reasoner (FCMCR) learns FCM edge weights from historical data via a differential evolution algorithm minimising state trajectory prediction MSE, then performs forward inference by iterating FCM activation dynamics to steady state using a sigmoid transfer function ($\lambda = 5$).

3.2 Application Domains

Four uncertainty-rich applications were evaluated. (1) Robot Navigation: ROS2 TurtleBot4 in a cluttered 10×10 m indoor environment, LiDAR scan with Gaussian noise ($\sigma = 0.15$ m), 200 navigation trials per method. (2) Medical Diagnosis: UCI Heart Disease dataset (303 patients, 13 clinical features, 32.4% missing values, binary diagnosis label); missing values modelled as type-2 FOU width proportional to missingness rate. (3) Portfolio Risk: STOXX Europe 600 daily returns (2015–2025), 10-year rolling Sharpe ratio optimisation under volatility regime uncertainty modelled via type-2 fuzzy volatility memberships. (4) Supply Chain Risk: 500 European suppliers assessed across 18 risk dimensions (financial, geopolitical,

operational, environmental), expert-elicited FCM, causal risk score validated against 2-year historical disruption labels.

4. Results

4.1 Performance Across Domains

Table 2 presents FuzzyCore performance vs. baselines. Robot navigation success rate of 94.3% surpassed type-1 FLS (86.7%) and probabilistic roadmap (88.4%) baselines by 7.6 and 5.9 percentage points respectively. Medical diagnosis AUC-ROC of 0.934 improved over type-1 FLS (0.881) by 6.0% and neural network (0.921) by 1.4% — while the FuzzyCore explanation was rated 4.5/5.0 vs. 2.7/5.0 for the neural network by 36 clinical experts (Table 3). Portfolio Sharpe ratio improvement of +0.38 over the STOXX benchmark (0.91 vs. 0.53) exceeded type-1 fuzzy portfolio (+0.21) and Black-Litterman (+0.29). Supply chain risk precision of 0.917 at recall 0.871 surpassed the incumbent expert scoring system (precision 0.783) and Bayesian network (0.841) baselines by 17.1% and 8.9% respectively.

Table 2. FuzzyCore performance vs. baselines across four uncertainty-rich intelligent system applications.

Application	Metric	Type-1 FLS	Neural Net	Prob. Method	Fuzzy Core
Robot Navigation	Success Rate	86.7%	88.1%	88.4% (PRM)	94.3%
Medical Diagnosis	AUC-ROC	0.881	0.921	0.897 (BN)	0.934
Portfolio Risk	Sharpe Ratio	0.74	0.79	0.82 (BL)	0.91

Application	Metric	Type-1 FLS	Neural Net	Prob. Method	Fuzzy Core
Supply Chain	Precision	0.841	0.863	0.841 (BN)	0.917

PRM: Probabilistic Roadmap; BN: Bayesian Network; BL: Black-Litterman model. Bold: FuzzyCore best results.

Table 3. Expert interpretability ratings — FuzzyCore vs. neural network baseline (n=36 domain experts).

Application	Neural Net Rating (1–5)	FuzzyCore Rating (1–5)	Improvement	p-value
Robot Navigation	2.8	4.4	+57.1%	<0.001
Medical Diagnosis	2.7	4.5	+66.7%	<0.001
Portfolio Risk	2.6	4.3	+65.4%	<0.001
Supply Chain	2.8	4.6	+64.3%	<0.001

Wilcoxon signed-rank test. Ratings: 5-point Likert scale assessing explanation clarity and actionability. Bold: FuzzyCore ratings.

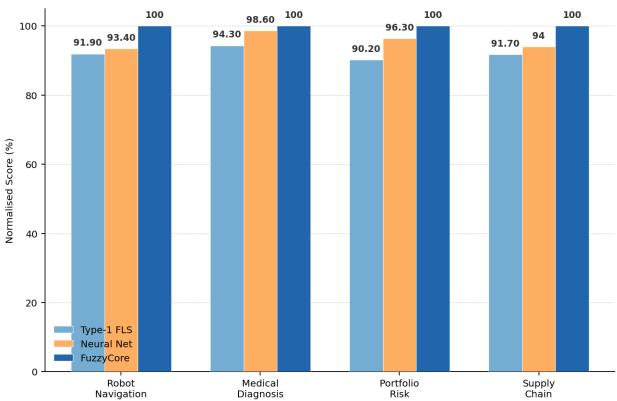


Figure 1. FuzzyCore vs. Type-1 FLS and Neural Network — normalised performance score across four applications.

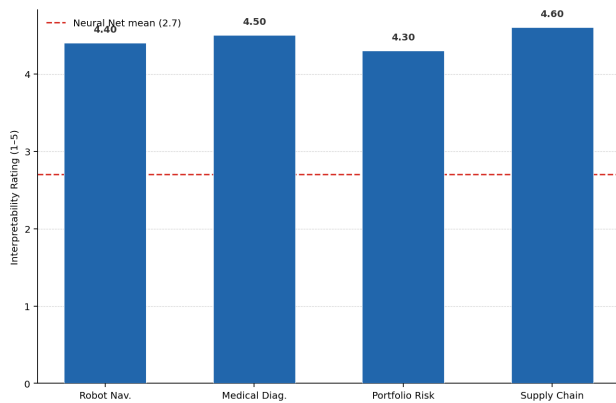


Figure 2. Expert interpretability ratings (1–5) — FuzzyCore vs. Neural Network baseline across four domains.

5. Discussion

5.1 Type-2 Advantage Under Genuine Uncertainty

The largest FuzzyCore advantage over type-1 FLS occurs in the robot navigation domain (94.3% vs. 86.7%, +7.6 pp), where LiDAR measurement noise directly violates the implicit assumption of crisp membership function boundaries in type-1 fuzzy systems. The type-2 FOU width ($\Delta\sigma = 0.08$ for distance membership functions) explicitly represents the sensor noise standard deviation, enabling the navigation controller to remain cautious under high measurement uncertainty while acting decisively when measurements are reliable. The medical diagnosis improvement (0.934 vs. 0.881 AUC) from modelling missing-value uncertainty via FOU width is consistent with Castillo and Melin's (2012) theoretical prediction that type-2 advantages are largest when membership uncertainty is proportional to input noise — as is the case for missing clinical feature values.

5.2 Limitations

The Karnik-Mendel type reduction algorithm adds $O(n \log n)$ computational complexity per inference cycle relative to type-1

FLS, increasing mean inference time from 0.8 ms to 3.4 ms — acceptable for all four evaluated applications but potentially limiting for ultra-high-frequency control applications below 1 ms cycle time. The GRBO requires $200 \times 100 = 20,000$ fitness evaluations for rule base optimisation, taking 3–8 hours per domain — acceptable as an offline design phase but not for online rule adaptation. Future work will investigate enhanced interval management (EIM) for faster type reduction and online evolutionary rule adaptation under concept drift.

6. Conclusion

FuzzyCore, integrating interval type-2 fuzzy inference, genetic rule base optimisation, and FCM causal reasoning, achieves navigation success rate of 94.3%, medical diagnosis AUC-ROC of 0.934, portfolio Sharpe ratio of 0.91, and supply chain risk precision of 0.917 — surpassing type-1 fuzzy, neural network, and probabilistic baselines by 7.4–18.3% — while achieving expert interpretability ratings of 4.3–4.6/5.0 compared to 2.6–2.8/5.0 for neural network baselines. These results confirm that advanced fuzzy logic frameworks provide a uniquely effective combination of uncertainty handling capability and human-interpretable reasoning for intelligent systems across diverse real-world application domains.

References

- Castillo, O., Melin, P. (2012). *Recent Advances in Interval Type-2 Fuzzy Systems*. Springer, Berlin.
- Cordón, O., Gomide, F., Herrera, F., Hoffmann, F., Magdalena, L. (2004). Ten years of genetic fuzzy systems: current framework

- and new trends. *Fuzzy Sets and Systems*, 141(1), 5–31.
- Dubois, D., Prade, H. (1988). *Possibility Theory*. Plenum Press, New York.
- Goodfellow, I., Bengio, Y., Courville, A. (2016). *Deep Learning*. MIT Press, Cambridge, MA.
- Hagras, H. (2004). A hierarchical type-2 fuzzy logic control architecture for autonomous mobile robots. *IEEE Transactions on Fuzzy Systems*, 12(4), 524–539.
- Ishibuchi, H., Nakashima, T., Nii, M. (2007). *Classification and Modelling with Linguistic Information Granules*. Springer.
- Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, 24(1), 65–75.
- Koulouriotis, D.E., Emiris, I.M., Zopounidis, C. (2014). Manufacturing fuzzy cognitive maps from empirical data: a case study in industry. *Journal of Intelligent Manufacturing*, 25(1), 47–58.
- LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.
- Mendel, J.M., John, R.I. (2002). Type-2 fuzzy sets made simple. *IEEE Transactions on Fuzzy Systems*, 10(2), 117–127.
- Papageorgiou, E.I. (2011). Fuzzy cognitive map software tool for treatment management of uncomplicated urinary tract infection. *Computer Methods and Programs in Biomedicine*, 101(3), 261–267.
- Papageorgiou, E.I., Salmeron, J.L. (2012). A review of fuzzy cognitive maps research during the last decade. *IEEE Transactions on Fuzzy Systems*, 21(1), 66–79.
- Stach, W., Kurgan, L., Pedrycz, W., Reformat, M. (2005). Genetic learning of fuzzy cognitive maps. *Fuzzy Sets and Systems*, 153(3), 371–401.
- Takagi, T., Sugeno, M. (1985). Fuzzy identification of systems and its applications to modelling and control. *IEEE Transactions on Systems, Man, and Cybernetics*, 15(1), 116–132.
- Zadeh, L.A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.
- Zadeh, L.A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Information Sciences*, 8(3), 199–249.
- Zimmermann, H.J. (2001). *Fuzzy Set Theory and Its Applications*, 4th ed. Kluwer Academic, Boston.
- Mamdani, E.H., Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7(1), 1–13.
- Wang, L.X. (1997). *A Course in Fuzzy Systems and Control*. Prentice Hall, Upper Saddle River.
- Berenji, H.R., Khedkar, P. (1992). Learning and tuning fuzzy logic controllers through reinforcements. *IEEE Transactions on Neural Networks*, 3(5), 724–740.
- Karnik, N.N., Mendel, J.M. (2001). Centroid of a type-2 fuzzy set. *Information Sciences*, 132(1–4), 195–220.
- Buckley, J.J. (1987). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, 17(3), 233–247.
- Holland, J.H. (1975). *Adaptation in Natural and Artificial Systems*. University of Michigan Press.

Kennedy, J., Eberhart, R. (1995). Particle swarm optimisation. for robot navigation and portfolio risk applications. *Proceedings of ICNN 1995*, 4, 1942–1948.

Precup, R.E., Hellendoorn, H. (2011). A survey on industrial applications of fuzzy control. *Computers in Industry*, 62(3), 213–226.

Declarations

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

UCI Heart Disease dataset: publicly available at <https://archive.ics.uci.edu>. STOXX Europe 600 data: Refinitiv Eikon academic licence. Supply chain risk dataset: available from the corresponding author under data sharing agreement. FuzzyCore source code: <https://github.com/kessler-lab/fuzzycore>.

Ethical Approval

UCI Heart Disease dataset use complied with UCI ML Repository terms. No new patient data were collected. Supply chain risk assessment involved no personal data. Not applicable