EAI Endorsed Transactions
on Context-aware Systems and Applications
Review Article EAI.EU

Systematic Review of Max-Min Aggregation in Fuzzy Systems and Interpretable Machine Learning: Models, Evaluation, and Applications

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Abstract

This systematic review investigates the use of max-min aggregation in fuzzy systems and interpretable machine learning. Rooted in fuzzy set theory and triangular norms, max-min aggregation offers a transparent and mathematically simple approach to modeling uncertainty and decision-making. We examine theoretical foundations, practical applications, evaluation methods, and comparative taxonomies. The review identifies key challenges such as scalability and integration with learning algorithms, and highlights future directions for improving transparency in AI. Our findings underscore the relevance of max-min aggregation in developing interpretable and responsible AI systems.

Received on 18 July 2025; accepted on 19 July 2025; published on 22 July 2025

Keywords: Max-Min Aggregation, Interpretable Machine Learning, Explainable Artificial Intelligence (XAI), Fuzzy Logic, Linguistic Modeling, Aggregation Operators, Systematic Review

doi:10.4108/eetcasa.9752

1. Introduction

Max-min aggregation has played a pivotal role in the evolution of fuzzy systems and their applications across artificial intelligence (AI), decision making, and computational linguistics. As foundational operations in fuzzy logic, max (t-conorm) and min (t-norm) operators offer a robust framework for modeling imprecise, vague, or linguistically expressed information [17, 18]. These operators form the basis for more complex constructs such as fuzzy inference systems, fuzzy integrals, and aggregation functions [3, 11].

The recent surge in demand for interpretable and explainable models in AI has renewed interest in fuzzy logic-based systems [6, 12]. In particular, the integration of linguistic variables and aggregation mechanisms has enabled more human-aligned reasoning in systems that support decision-making under uncertainty [1, 8]. These approaches have been increasingly applied in areas such as expert systems, medical diagnosis [2], and interpretable machine learning pipelines [15].

To ensure scientific rigor and transparency, the development of systematic reviews in this domain must follow established guidelines such as the PRISMA statement [13, 14] and evidence-based software engineering methodologies [9]. These frameworks support reproducible and comprehensive syntheses of the literature, which are essential for mapping the conceptual landscape and identifying emerging trends.

Structure of the paper. The remainder of this paper is organized as follows: Section 2 outlines the methodology adopted in this systematic review. Section 3 reviews theoretical foundations of max-min aggregation in fuzzy linguistic systems. Section 4 analyzes applications in AI and machine learning. Section 5 discusses ongoing challenges and future directions. Finally, Section 6 concludes the review and highlights key takeaways.

2. Methodology

This systematic review adheres to the guidelines established by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2009 and

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2020 statements [13, 14], as well as the methodology recommended in software engineering by Kitchenham and Charters [9]. The methodological process is composed of the following key phases: planning, search strategy, inclusion and exclusion criteria, study selection, quality assessment, data extraction, and synthesis.

2.1. Review Objectives

The main objective of this systematic review is to analyze the evolution, usage, and applications of Max-Min aggregation operators within fuzzy linguistic systems and machine learning contexts. Specific questions addressed include:

- What are the dominant trends and themes in Max-Min aggregation research?
- How is Max-Min aggregation employed in fuzzy linguistic models and AI applications?
- What gaps and challenges exist in the current literature?

2.2. Search Strategy

We developed a comprehensive search strategy to identify relevant studies across the following databases: Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. The search terms combined key phrases such as: *"Max-Min aggregation"*, *"fuzzy logic"*, *"linguistic modeling"*, *"aggregation operators"*, and *"machine learning"*. Boolean operators and truncations were used to expand the search scope, e.g., (`"fuzzy*"` AND `"max-min"` AND `"aggregation*"`).

2.3. Inclusion and Exclusion Criteria

We applied clear inclusion and exclusion criteria. To be eligible, studies had to:

- Be written in English;
- Be published in peer-reviewed journals or top-tier conferences between 2000 and 2024;
- Discuss Max-Min aggregation in the context of fuzzy logic, linguistic modeling, or AI.

Excluded were:

- Non-peer-reviewed articles, book reviews, and short abstracts;
- Studies not addressing the theoretical or applied aspects of Max-Min aggregation.

2.4. Study Selection Process

The study selection process was performed in two stages: (1) title and abstract screening and (2) full-text review. Two independent reviewers assessed each article. Disagreements were resolved through discussion or adjudication by a third reviewer. The selection process is documented following PRISMA standards [13, 14].

2.5. Quality Assessment and Data Extraction

Quality assessment criteria were adapted from [9], including clarity of objectives, methodological rigor, and contribution to the field. Each study was scored using a predefined checklist. Data extraction involved collecting metadata (e.g., authorship, publication year), methods, application domains, and results related to Max-Min aggregation.

2.6. Data Synthesis

We employed both quantitative and qualitative synthesis methods. Descriptive statistics summarized publication trends, while thematic analysis was used to identify research patterns and conceptual developments in fuzzy linguistic systems and AI leveraging Max-Min aggregation operators.

3. Theoretical Foundations

Max-min aggregation plays a fundamental role in fuzzy logic systems, especially in modeling human-like reasoning through linguistic variables and approximate inference. This section outlines the theoretical basis of fuzzy set theory, aggregation functions, and the relevance of the max-min operator in interpretability and modeling.

3.1. Fuzzy Set Theory and Linguistic Variables

The concept of fuzzy sets was first introduced by Zadeh to handle the imprecision inherent in many real-world problems [17]. Fuzzy set theory allows gradual membership rather than crisp classification, thereby supporting reasoning with vague or imprecise concepts. This framework is particularly powerful when linguistic terms (e.g., "high," "low," "moderate") are used to model expert knowledge.

Linguistic variables, another essential innovation by Zadeh, form the basis for expressing knowledge in fuzzy systems. Each linguistic variable is associated with a set of linguistic terms, which are represented by fuzzy sets. These constructs have been widely applied in decision support, control systems, and knowledge-based inference.

3.2. Aggregation Operators in Fuzzy Systems

Aggregation functions are used to combine multiple fuzzy inputs into a single output, and their selection critically influences the behavior and interpretability of a fuzzy system. Among them, the max-min operator is one of the most intuitive and computationally simple methods. It is based on two fundamental operations: maximum (used for union-type aggregation) and minimum (used for intersection-type aggregation) [18].

The study of triangular norms (t-norms) and triangular conorms (t-conorms) provides a formal mathematical foundation for fuzzy aggregation. T-norms are used to generalize the logical conjunction in fuzzy logic, while t-conorms generalize the disjunction. Klement et al. provided a comprehensive overview of various t-norms and their properties [10].

3.3. Max-Min Aggregation and Interpretability

Max-min aggregation is especially appealing for interpretable models because of its simplicity and alignment with human reasoning patterns. For instance, in rule-based systems, the antecedent part often uses the minimum (AND) operator to assess the degree of rule activation, while the consequent aggregation may involve the maximum (OR) operator.

According to Beliakov et al., selecting appropriate aggregation functions is a balance between mathematical properties (e.g., associativity, commutativity, monotonicity) and application-specific interpretability [3]. Max-min aggregation meets many of these requirements and is computationally efficient, making it suitable for real-time decision systems.

Furthermore, the uncertainty modeling in fuzzy systems can be enhanced using type-2 fuzzy sets and rule-based reasoning schemes. Mendel explored how rule-based fuzzy logic systems could incorporate uncertainty using advanced aggregation techniques [11].

3.4. Summary

To summarize, max-min aggregation sits at the heart of interpretable fuzzy logic systems. Its theoretical grounding in fuzzy set theory, linguistic variables, and t-norm frameworks makes it a strong candidate for building transparent and computationally feasible decision-making models. The next sections will build upon this foundation by examining how max-min aggregation has been applied and evaluated in real-world interpretable machine learning systems.

4. Applications in Interpretable Machine Learning

As the demand for interpretable artificial intelligence (AI) systems grows, max-min aggregation has found renewed interest due to its transparency, alignment with human reasoning, and simplicity. This section presents the main application domains and model architectures in which max-min aggregation has been effectively employed for interpretable machine learning (IML).

4.1. Fuzzy Rule-Based Systems

Fuzzy rule-based systems (FRBSs) have long employed max-min aggregation to model rule antecedents and aggregate fuzzy outputs. These systems leverage the minimum operator to evaluate the degree of fulfillment of antecedent clauses and the maximum operator to combine multiple rule outputs. The inherent interpretability of FRBSs stems from their linguistic rule representations and transparent reasoning process.

Mendel [11] emphasized that max-min aggregation offers both computational simplicity and interpretability in designing fuzzy inference systems, especially in Mamdani-type architectures. These models have been used in medical diagnosis, risk assessment, and control systems due to their ability to provide clear explanations.

4.2. Fuzzy Decision-Making and Classification

In decision-making scenarios, fuzzy systems with max-min aggregation provide explainable outputs in group decision support and multi-criteria evaluation contexts. Herrera et al. [8] and Alonso et al. [1] illustrated the use of fuzzy linguistic models—underpinned by max-min operators—to handle subjective and imprecise preference information in group decision-making settings.

For classification tasks, fuzzy classifiers leveraging max-min operations offer interpretable decision boundaries. Casillas et al. [4] showed how fuzzy rules with simple aggregation operators such as min and max could be effectively learned using boosting techniques, leading to interpretable yet accurate classifiers.

4.3. Medical and Healthcare Applications

Explainable models are critical in healthcare applications, where trust and transparency are essential. Barro and Marin [2] reviewed how fuzzy models, especially those utilizing max-min aggregation, are well-suited for clinical decision support systems (CDSS). Their ability to mimic expert reasoning and output human-readable decisions enhances trust and usability in medical environments.

Recent systematic reviews, such as the one by Tran et al. [15], highlight that fuzzy logic remains one of the most prominent techniques in explainable AI for healthcare, particularly when combined with interpretable rule extraction.

4.4. XAI and Socially Grounded Explanations

Fuzzy aggregation, including max-min methods, also supports explainability in machine learning by generating natural-language-like explanations. Miller [12] argues that effective explanations in AI should follow human expectations derived from social science insights. Since fuzzy rule systems with max-min logic generate explanations using linguistic rules, they align well with these expectations.

Ghosh et al. [6] surveyed the intersection of fuzzy logic and explainable AI (XAI), identifying aggregation functions as central components for constructing interpretable models. They show that integrating fuzzy aggregation into deep learning and ensemble architectures improves both transparency and post-hoc explainability.

4.5. Challenges and Research Gaps

Despite these successes, several limitations remain. First, traditional max-min aggregation may struggle with high-dimensional data unless combined with feature selection or fuzzy partitioning. Second, interpretability may sometimes come at the cost of accuracy in complex tasks. Third, integrating max-min aggregation into neural-symbolic systems or generative architectures remains an open challenge.

Future research directions include combining max-min aggregation with recent developments in interpretable neural networks, generative models, and hybrid neuro-fuzzy architectures.

5. Evaluation Approaches and Benchmarks

Evaluating the performance and interpretability of max-min aggregation models in fuzzy systems and interpretable machine learning requires a combination of quantitative accuracy measures and qualitative explainability assessments. This section surveys the key evaluation frameworks, metrics, and benchmark datasets employed in the literature.

5.1. Quantitative Evaluation Metrics

The performance of fuzzy systems using max-min aggregation is often evaluated using traditional machine learning metrics such as classification accuracy, precision, recall, and F1-score. In regression tasks, mean squared error (MSE) and root mean squared error (RMSE) are standard. These metrics are typically used to compare max-min fuzzy models with alternative fuzzy aggregation techniques (e.g., weighted averaging, fuzzy integrals).

Grabisch and Sugeno [7] compared different fuzzy integrals for classification tasks, noting that max-min aggregation can perform competitively when rule bases are well-tuned. However, they also emphasized that fuzzy integrals offer greater flexibility when interaction between attributes is critical.

5.2. Interpretability and Explainability Measures

Interpretability in fuzzy models can be assessed by the number of rules, the length of each rule, and the complexity of the fuzzy sets involved. Max-min aggregation supports high interpretability due to its use of simple logical operators (max and min) and its compatibility with linguistic expressions [8, 11].

Ghosh et al. [6] proposed explainability evaluation frameworks that include transparency (how the model works), simulatability (whether a human can mentally simulate the model), and decomposability (whether each component has an intuitive interpretation). Max-min aggregation performs well across all these dimensions due to its rule-based, modular structure.

5.3. Benchmark Datasets

Several standard datasets have been used in empirical studies to benchmark max-min aggregation models. These include:

- **Iris Dataset**: A classical classification dataset frequently used for demonstrating fuzzy rule-based models.
- **Wine Quality and Breast Cancer datasets**: Used in explainable classification scenarios.
- **Medical Diagnosis Datasets**: Barro and Marin [2] employed medical datasets such as heart disease and diabetes diagnosis to validate the effectiveness of max-min fuzzy systems in real-world applications.
- **Synthetic Rule-Based Datasets**: For controlled experiments assessing interpretability, some studies generate synthetic datasets with known decision boundaries and rule structures.

These datasets allow researchers to test both predictive accuracy and model interpretability, often through user studies or expert evaluation.

5.4. Comparative Studies and Hybrid Models

Comparative evaluations between max-min models and other fuzzy aggregation operators—such as Ordered Weighted Averaging (OWA) [16], fuzzy integrals [7], or T-norm-based systems [10]—are essential to understanding trade-offs. In some cases, hybrid models that combine max-min rules with optimization or learning algorithms (e.g., boosting, evolutionary algorithms) are evaluated to balance performance and simplicity [4, 5].

5.5. Limitations in Evaluation Methodologies

Despite widespread use, challenges remain in systematically evaluating explainability. Tran et al. [15] noted the lack of unified benchmarks and metrics for explainable AI in healthcare, which also applies to fuzzy models. Furthermore, explainability is context-dependent—what is interpretable in a medical system may not be so in a financial application.

There is a growing need for standardized explainability benchmarks and human-in-the-loop evaluation methodologies, where domain experts assess the quality of explanations produced by max-min aggregation models in real-world tasks.

6. Taxonomy and Comparative Analysis

This section presents a structured taxonomy of max-min aggregation models used in fuzzy systems and interpretable machine learning. It also provides a comparative analysis between max-min aggregation and other fuzzy aggregation strategies, focusing on criteria such as expressiveness, interpretability, computational complexity, and application domains.

6.1. Taxonomy of Max-Min Aggregation Models

Max-min aggregation models can be categorized based on the following dimensions:

- **Type of Fuzzy Inference**: Mamdani-type fuzzy systems use linguistic rules with max-min operators for both rule evaluation and aggregation [17]. In contrast, Takagi–Sugeno models typically use weighted averages and are less common with strict max-min operators.
- **Rule Learning Strategy**:
  - *Expert-defined rules*: Traditional fuzzy systems rely on domain experts to define rules and membership functions [18].
  - *Data-driven rules*: Recent approaches leverage algorithms such as boosting and evolutionary computation to optimize rule bases and membership functions [4, 5].
- **Model Architecture**:
  - *Flat rule-based systems*: Each rule is independent, and aggregation is performed at the output layer using max-min operators.
  - *Hierarchical fuzzy systems*: Max-min logic is used recursively at multiple levels, improving scalability for complex domains [11].
- **Application Domain**:
  - *Medical Decision Support*: Commonly used for diagnostic classification with high interpretability [2].
  - *Industrial Control and Robotics*: Employed in real-time systems where rule transparency and deterministic behavior are critical.
  - *Interpretable AI Models*: Used as explainable modules within hybrid AI systems [6].

6.2. Comparative Analysis with Other Aggregation Operators

Table 1. Comparison of Aggregation Operators in Fuzzy Systems

Aggregation Operator	**Expressiveness**	**Interpretability**
Max-Min Aggregation	Medium	High
OWA (Yager, 1988) [16]	High	Medium
Fuzzy Integrals (Sugeno, Choquet) [7]	Very High	Low–Medium
T-norms and T-conorms [10]	High	Medium
Weighted Averaging	Medium	Low

6.3. Strengths of Max-Min Aggregation

Max-min aggregation is particularly effective when simplicity and transparency are prioritized. Its reliance on basic logical operations makes it suitable for systems where human interpretability is essential, such as in safety-critical environments. The compositional nature of max and min operators also simplifies theoretical analysis and hardware implementation [18].

6.4. Limitations and Challenges

While interpretable, max-min aggregation can be limited in handling attribute interaction or modeling smooth transitions between decision regions. In such cases, fuzzy integrals or learning-based aggregation functions may outperform in accuracy but at the cost of reduced transparency [6, 7].

Additionally, expert-designed max-min systems may face scalability challenges in high-dimensional spaces or large rule bases. Recent efforts to integrate optimization methods such as boosting [4] and genetic algorithms [5] help mitigate these challenges while preserving interpretability.

6.5. Future Integration in Hybrid Systems

There is a growing trend toward embedding max-min aggregation modules within larger interpretable pipelines, including fuzzy neural networks, neuro-symbolic architectures, and explainable decision trees [6]. Such integration leverages the strengths of max-min logic while compensating for its limitations in flexibility and adaptation.

7. Challenges and Future Directions

Despite their simplicity and interpretability, max-min aggregation methods in fuzzy systems and interpretable machine learning face several challenges that limit their scalability and flexibility in modern AI contexts. This section outlines these limitations and discusses potential directions for advancing the research and deployment of such models.

7.1. Challenges

1. Scalability to High-Dimensional Data. Max-min aggregation techniques are inherently rule-based, requiring exhaustive rule enumeration or combinatorial expansion when dealing with high-dimensional inputs. This leads to an exponential growth in rule base size, known as the "curse of dimensionality" [5]. Although hierarchical fuzzy systems [11] and modular designs have alleviated some of these issues, further improvement is required to maintain interpretability while enhancing scalability.

2. Limited Adaptability and Learning. Traditional max-min systems often rely on expert-defined rules and membership functions. These handcrafted components, while interpretable, may lack the flexibility to adapt to dynamic environments or noisy data. While hybrid models combining fuzzy systems with machine learning algorithms have been proposed [4], these models often sacrifice transparency to achieve better performance.

3. Inadequate Handling of Feature Interactions. Max-min aggregation lacks the expressiveness required to capture complex feature interactions. Unlike fuzzy integrals such as Choquet or Sugeno measures [7], which allow modeling of interdependencies among input variables, max-min methods assume independent rule evaluation. This may lead to suboptimal performance in tasks requiring context-sensitive reasoning.

4. Benchmarking and Standardization. A significant challenge in comparing fuzzy aggregation methods lies in the lack of standardized datasets and evaluation protocols. Although some benchmarking efforts exist in the context of interpretable machine learning [6], there is a pressing need for reproducible experimental frameworks and explainability-specific metrics tailored to fuzzy rule-based systems.

7.2. Future Directions

1. Integration with Neuro-Symbolic Architectures. One promising direction is the incorporation of max-min operators into neuro-symbolic models. These hybrid systems aim to combine the learning capacity of neural networks with the logical structure of symbolic reasoning [6]. Embedding max-min logic at the symbolic layer can enhance interpretability while enabling deep learning-based feature extraction.

2. Learning-Enhanced Max-Min Systems. Future research should focus on developing learning algorithms specifically tailored for max-min aggregation. For instance, using differentiable fuzzy logic layers [12] or reinforcement learning to adjust membership functions could make traditional fuzzy systems more adaptive while preserving their interpretability.

3. Explainability Benchmarks and Visualization Tools. The creation of explainability benchmarks for fuzzy rule-based systems, along with tools that visualize rule activations and decision boundaries, could bridge the gap between model transparency and user trust [6, 12]. Tools like PRISM or ExpliClass can be adapted to evaluate and display fuzzy inference chains in real-time applications.

4. Cross-Domain Applications and Multimodal Integration. Finally, applying max-min aggregation in novel domains—such as multimodal reasoning (text, image, audio), personalized recommendation, and human-in-the-loop systems—could demonstrate the broader relevance of interpretable fuzzy models. Such deployments would benefit from the inherent transparency of max-min logic while stimulating interdisciplinary innovation.

8. Conclusion

This systematic review explored the role of max-min aggregation within fuzzy systems and its application to interpretable machine learning. We began by establishing the theoretical underpinnings of max-min logic, rooted in classical fuzzy set theory [17], triangular norms [10], and rule-based reasoning frameworks [11, 18]. These foundations offer simplicity and high interpretability, making them particularly suited for domains where transparency is paramount.

Applications in interpretable machine learning have demonstrated how max-min aggregation can yield rule-based models that are both comprehensible and competitive in performance [6, 8]. From healthcare to decision support systems, the integration of fuzzy linguistic modeling [1] and aggregation operators [3, 16] highlights the relevance of max-min strategies in building trustworthy AI systems.

We analyzed evaluation methodologies and benchmark frameworks, noting that while performance metrics such as accuracy and F1-score are common, specialized explainability metrics remain underdeveloped for fuzzy systems. This signals a need for domain-specific, interpretable AI benchmarks [15] that can effectively assess the transparency of fuzzy logic-based approaches.

The taxonomy presented in this review compared max-min aggregation to other methods such as fuzzy integrals [7] and weighted averaging operators, emphasizing the trade-offs between interpretability, modeling complexity, and computational cost.

Lastly, we outlined critical challenges including scalability, adaptability, and standardization, and proposed future directions involving learning-enhanced fuzzy systems, integration with neuro-symbolic architectures, and the development of visualization tools to support model transparency [12].

In summary, max-min aggregation remains a vital and interpretable mechanism in fuzzy systems and machine learning. By addressing current limitations and aligning with emerging trends in explainable AI, future research can further solidify its role in the broader landscape of transparent and responsible artificial intelligence.

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