Hybrid-FLBCC: Virtual Machine Consolidation in Cloud Infrastructures Exploring Flexible Computing

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Outline

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Cloud Computing Sustainability Challenges

- Cloud Computing is undergoing rapid expansion and transformation.
- In 2022, data centers consumed approximately **460 TWh**; the IEA projects this will exceed **1,000 TWh** by 2026, driven by AI and cryptocurrency demands.
- This energy demand challenges key **UN Sustainable Development Goals**: affordable and clean energy, responsible consumption, and climate action.
- Major cloud providers are investing in renewable energy and green technologies.
- This scenario highlights the urgency of energy-aware strategies such as **server consolidation** in resource management.
- Server consolidation involves identifying overloaded and underutilized hosts, selecting VM migration strategies, and reallocating resources to alternative hosts.

Objective

- Propose Hybrid-FLBCC as an evolution of Int-FLBCC
- Combine IvFL with AI techniques to improve VM consolidation
- Apply FRBCS and feature selection to support resource-aware decisions
- Improve energy efficiency and classification performance
- Promote interpretable and cost-effective fuzzy systems

Outline

Why to use Fuzzy Logic in VM Consolidation?

Fuzzy Logic in VM Consolidation

- FL supports **decision-making** in uncertain and dynamic VM consolidation scenarios.
- **Interval-valued Fuzzy Set** (IvFS), proposed by Sambuc in 1975, introduces interval-valued membership functions.
- It enables reasoning under **uncertainties and tolerate imprecision**.
- FL is the basis of Fuzzy Rule-Based Classification Systems (FRBCS).

What is a Fuzzy Rule-Based Classification System?

Fuzzy Rule-Based Classification Systems

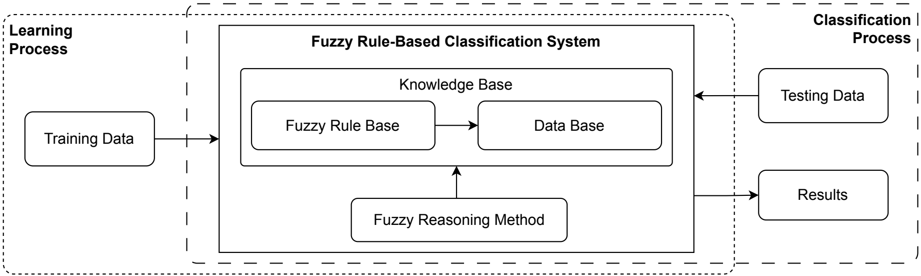


Figure: Fuzzy Rule-Based Classification process from training to testing

FRBCS considered in this study:

- **FARC-HD:** Efficient for high-dimensional data; uses genetic tuning and rule selection.
- **Chi Algorithm:** Generates one fuzzy rule per instance using fuzzy partitions.
- **FURIA:** Produces unordered fuzzy rules for flexible classification boundaries.
- **IVTURS:** Enhances FARC-HD with interval-valued fuzzy reasoning and evolutionary optimization.

Where do we apply this?

Int-FLBCC - Interval Fuzzy Load Balancing for Cloud Computing

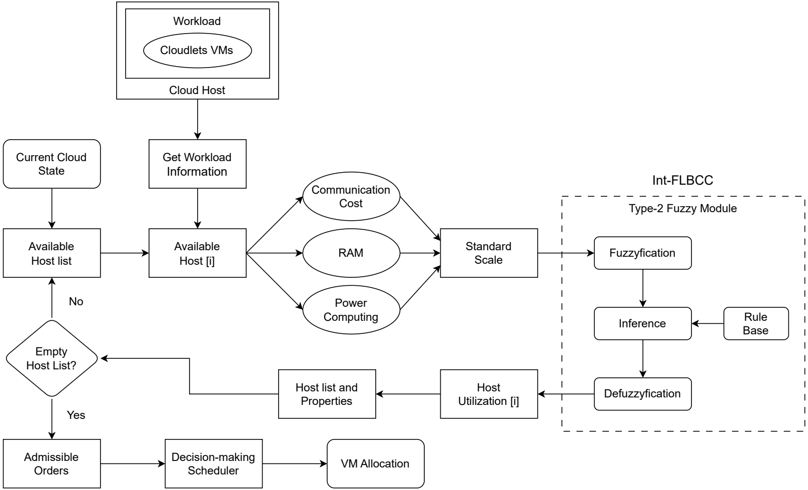


Figure: Overview of Int-FLBCC Approach.

Int-FLBCC - Interval Fuzzy Load Balancing for Cloud Computing

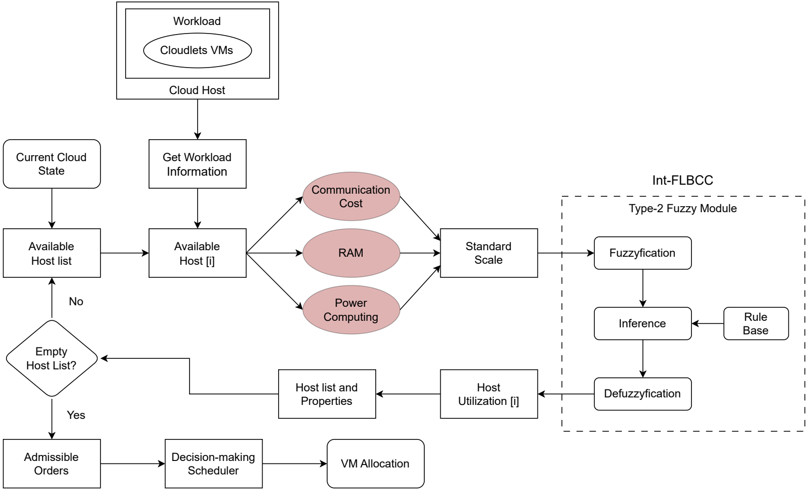


Figure: Overview of Int-FLBCC Approach.

Outline

From Int-FLBCC to Hybrid-FLBCC

- Integrates ML for feature selection and adaptive rule generation
- Adjusts allocation policies to current workloads
- Refines decision-making with updated fuzzy models

How did we do this?

Feature Selection Strategy

- Feature selection via Sequential Forward Selection (SFS)
- Goal: eliminate correlated variables, improve accuracy
- Classification models: FARC-HD, Chi, FURIA, IVTURS
- Evaluation: AUC metric with 10-fold cross-validation
- We use the KEEL software tool

Dataset details

Dataset

- Based on CloudSim simulations with PlanetLab traces
- 24h simulation, data every 300s ($\sim$320,000 instances)
- CPU, memory, bandwidth, storage, energy, MIPS
- Labels: underutilized, regular, overutilized
- 16 scenarios (AP×SP combinations)

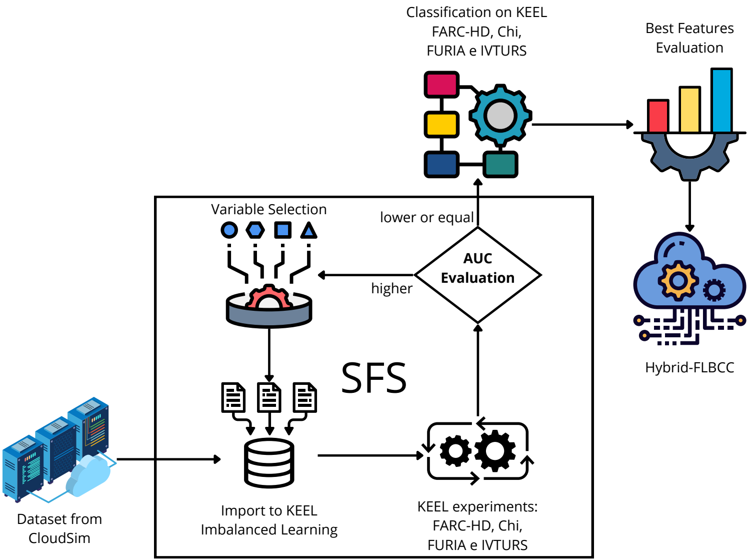
VM Allocation Policies

- Interquartile Range (IQR)
- Local Regression (LR)
- Local Regression Robust (LRR)
- Median Absolute Deviation (MAD)

VM Selection Policies

- Maximum Correlation (MC)
- Minimum Migration Time (MMT)
- Minimum Utilization (MU)
- Random Selection (RS)

Feature Selection's Process



Outline

What results did we get?

Evaluation Results of Variable Selection for IQR

SP	FRBCS	Variables						AUC
MC	**FURIA**	cpu	energy	mips	-	-	-	**0.9851**
	IVTURS	cpu	bw	mips	-	-	-	0.8812
	FURIA*	cpu	mem	bw	-	-	-	**0.9209**
	IVTURS*	cpu	mem	bw	-	-	-	0.8419
MMT	**FURIA**	cpu	energy	mem	storage	-	-	**0.9954**
	IVTURS	cpu	bw	mips	mem	-	-	0.9301
	FURIA*	cpu	mem	bw	-	-	-	**0.9292**
	IVTURS*	cpu	mem	bw	-	-	-	0.8039
MU	**FURIA**	mips	energy	cpu	-	-	-	**0.9885**
	FURIA*	cpu	mem	bw	-	-	-	**0.8464**
RS	**FURIA**	cpu	energy	mips	bw	mem	-	**0.9880**
	IVTURS	cpu	storage	bw	energy	-	-	0.8648
	FURIA*	cpu	mem	bw	-	-	-	**0.9252**
	IVTURS*	cpu	mem	bw	-	-	-	0.7799

*Considering the configuration defined in Int-FLBCC.

Evaluation Results of Variable Selection for LR

SP	FRBCS	Variables						AUC
MC	**FURIA**	cpu	energy	storage	mips	-	-	**0.9916**
	IVTURS	cpu	bw	mips	mem	-	-	0.9644
	FURIA*	cpu	mem	bw	-	-	-	**0.9771**
	IVTURS*	cpu	mem	bw	-	-	-	0.9227
MMT	**FURIA**	cpu	energy	storage	mem	-	-	**0.9958**
	IVTURS	cpu	bw	mips	mem	-	-	0.9644
	FURIA*	cpu	mem	bw	-	-	-	**0.9662**
	IVTURS*	cpu	mem	bw	-	-	-	0.9015
MU	**FURIA**	mips	energy	cpu	mem	bw	-	**0.9945**
	IVTURS	cpu	mem	bw	storage	energy	mips	0.8349
	FURIA*	cpu	mem	bw	-	-	-	**0.9484**
	IVTURS*	cpu	mem	bw	-	-	-	0.7621
RS	**FURIA**	mem	energy	cpu	mips	-	-	**0.9894**
	IVTURS	cpu	mem	bw	storage	energy	mips	0.8349
	FURIA*	cpu	mem	bw	-	-	-	**0.9778**
	IVTURS*	cpu	mem	bw	-	-	-	0.9135

*Considering the configuration defined in Int-FLBCC.

Evaluation Results of Variable Selection for LRR

SP	FRBCS	Variables						AUC
MC	**FURIA**	cpu	energy	storage	mips	-	-	**0.9916**
	IVTURS	cpu	bw	mips	mem	-	-	0.9644
	FURIA*	cpu	mem	bw	-	-	-	**0.9771**
	IVTURS*	cpu	mem	bw	-	-	-	0.9227
MMT	**FURIA**	cpu	energy	storage	mem	-	-	**0.9958**
	IVTURS	cpu	bw	mips	mem	storage	-	0.9492
	FURIA*	cpu	mem	bw	-	-	-	**0.9662**
	IVTURS*	cpu	mem	bw	-	-	-	0.9015
MU	**FURIA**	mips	energy	cpu	mem	bw	-	**0.9945**
	IVTURS	cpu	bw	mips	mem	storage	-	0.9492
	FURIA*	cpu	mem	bw	-	-	-	**0.9484**
	IVTURS*	cpu	mem	bw	-	-	-	0.7621
RS	**FURIA**	cpu	energy	storage	-	-	-	**0.9920**
	IVTURS	cpu	bw	mips	mem	storage	-	0.9595
	FURIA*	cpu	mem	bw	-	-	-	**0.9744**
	IVTURS*	cpu	mem	bw	-	-	-	0.9054

*Considering the configuration defined in Int-FLBCC.

Evaluation Results of Variable Selection for MAD

SP	FRBCS	Variables						AUC
MC	**FURIA**	cpu	energy	mips	-	-	-	**0.9870**
	FURIA*	cpu	mem	bw	-	-	-	**0.8648**
MMT	**FURIA**	cpu	energy	mem	storage	-	-	**0.9952**
	FURIA*	cpu	mem	bw	-	-	-	**0.8735**
	IVTURS*	cpu	mem	bw	-	-	-	0.5649
MU	**FURIA**	cpu	energy	mem	bw	-	-	**0.9906**
	FURIA*	cpu	mem	bw	-	-	-	**0.7362**
RS	**FURIA**	mips	energy	cpu	mem	storage	-	**0.9873**
	FURIA*	cpu	mem	bw	-	-	-	**0.8339**

*Considering the configuration defined in Int-FLBCC.

Experimental Results Overview

- Hybrid-FLBCC features consistently outperformed Int-FLBCC in all scenarios.
- FURIA showed the best classification performance across combinations.
- CPU is the most recurrent variable but not always the most important.
- SFS selected different subsets, optimizing performance per scenario.
- Results highlight input sensitivity and improved adaptability in Hybrid-FLBCC.

What are the improvements for the fuzzy system?

Membership Functions Samples

Variable	Linguistic Term	Chi Triangular MF			FARC-HD Triangular MF			FURIA Trapezoidal MF				IVTURS Triangular MF		
Bandwidth	Low	-0.0500	0.0000	0.0500	-0.0725,	-0.0225,	0.0275	-	-	-	-	[-0.05, 0.05]	[-0.075, 0.075]	[-0.075, 0.075]
	Medium	0.0000	0.0500	0.1000	-0.0139,	0.0312,	0.0812	-	-	-	-	[0.0, 0.1]	[-0.025, 0.125]	[-0.025, 0.125]
	High	0.0500	0.1000	0.1500	0.0723,	0.1217,	0.1717	-	-	-	-	[0.05, 0.15]	[0.025, 0.175]	[0.025, 0.175]
CPU	Low	-0.4994	0.0000	0.4994	-0.4616,	0.0704,	0.5698	$-\infty$	0	0.1250	0.2987	[-0.4994, 0.4994]	[-0.7492, 0.7492]	[-0.7492, 0.7492]
	Medium	0.0000	0.4994	0.9989	0.0303,	0.494,	0.9934	0.1637	0.3480	0.6432	0.8540	[0.0, 0.9989]	[-0.2497, 1.2486]	[-0.2497, 1.2486]
	High	0.4994	0.9989	1.4983	0.6425,	1.1419,	1.6414	0.5659	0.8705	1	∞	[0.4994, 1.4983]	[0.2497, 1.7481]	[0.2497, 1.7481]
Energy	Low	-	-	-	-	-	-	$-\infty$	$-\infty$	0	253.7326	[-23999.55, 23999.55]	[-35999.33, 35999.33]	[-35999.33, 35999.33]
	Medium	-	-	-	-	-	-	0	253.7326	697.0520	1	[0.0, 47999.10]	[-11999.78, 59998.88]	[-11999.78, 59998.88]
	High	-	-	-	-	-	-	697.0520	1	∞	∞	[23999.55, 71998.66]	[11999.78, 83998.43]	[11999.78, 83998.43]
Memory	Low	-0.2026	0.0000	0.2026	-0.2850,	-0.0067,	0.1959	-	-	-	-	-	-	-
	Medium	0.0000	0.2026	0.4052	-0.0237,	0.1789,	0.3815	-	-	-	-	-	-	-
	High	0.2026	0.4052	0.6078	0.1966,	0.3992,	0.6018	-	-	-	-	-	-	-
Storage	Low	-0.0571	0.0000	0.0571	-0.0736,	-0.0165,	0.1892	$-\infty$	0	0.2506	0.5025	[-0.0571, 0.0571]	[-0.0857, 0.0857]	[-0.0857, 0.0857]
	Medium	0.0000	0.0571	0.1142	-0.0046,	0.0501,	0.1072	0.2506	0.5025	0.5541	0.5820	[0.0, 0.1142]	[-0.0286, 0.1428]	[-0.0286, 0.1428]
	High	0.0571	0.1142	0.1713	0.0750,	0.1321,	0.1892	0.0554	0.0582	1	∞	[0.0571, 0.1713]	[0.0286, 0.1999]	[0.0286, 0.1999]

Rule Interpretability

FARC-HD Sample Rules

```
bw IS L_0(3): normal CF: 1.0

cpu IS L_1(3) AND mem IS L_1(3) AND storage IS L_1(3): under CF: 0.5347
```

Chi Sample Rules

```
cpu IS L_0 AND mem IS L_0 AND bw IS L_0 AND storage IS L_0: normal with Rule Weight: 1.0

cpu IS L_1 AND mem IS L_2 AND bw IS L_2 AND storage IS L_0: normal with Rule Weight: 0.5910
```

FURIA Sample Rules

```
(cpu >= 0.1637(-> 0.1599)) and (cpu <= 0.1637 (-> 0.1637)) => class=normal (CF = 1.0)
(cpu >= 0.0021(-> 0)) and (storage <= 0.0025 (-> 0.0050)) and (energy <= 0(->253.7326)) and
    (cpu <= 0.0077(-> 0.0083))=>class=under (CF = 0.99)
```

IVTURS Sample Rules

```
bw IS L_0(3): normal CF: [1.0, 1.0]

energy IS L_0(3) AND storage IS L_0(3) AND bw IS L_2(3): under CF: [0.4182, 0.4238]
```

Hybrid-FLBCC Improvements

- Hybrid-FLBCC adapts fuzzy configurations to each policy scenario.
- Uses data-driven rule bases instead of fixed expert-defined rules.
- Integrates FRBCS performance to refine decision-making.
- Combines FURIA's precision with IVTURS's uncertainty handling.
- New rule bases simplify fuzzy implementation and may reduce computational cost.

And what to do with all this?

Hybrid-FLBCC

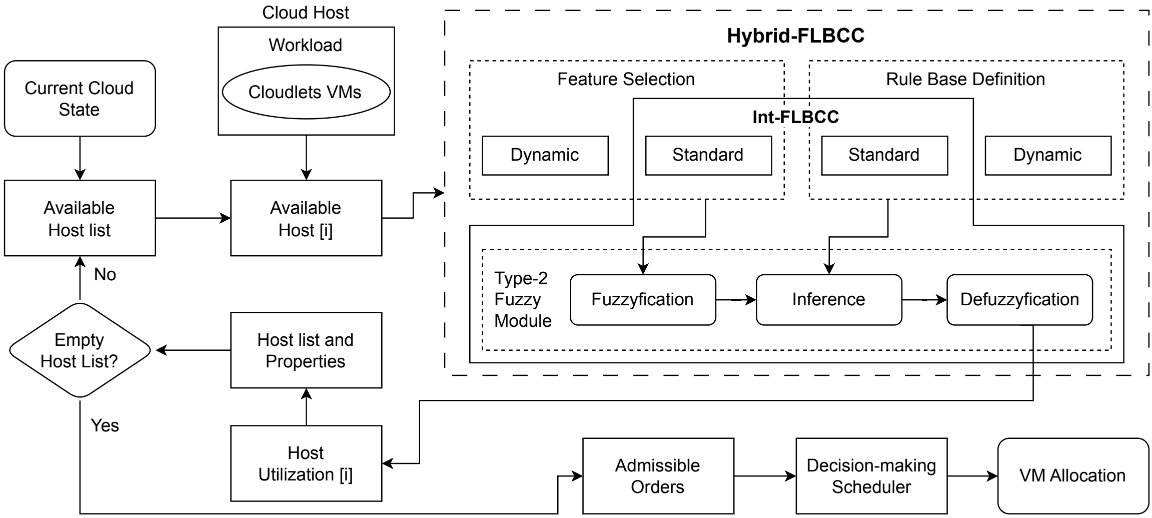
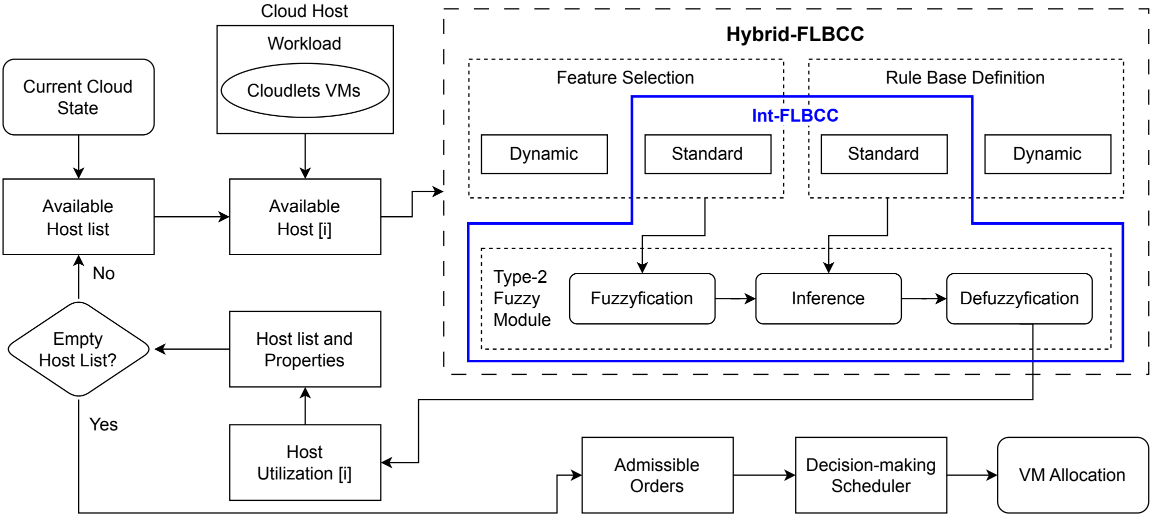


Figure: Overview of the Hybrid-FLBCC Extending the Int-FLBCC Approach.

Hybrid-FLBCC



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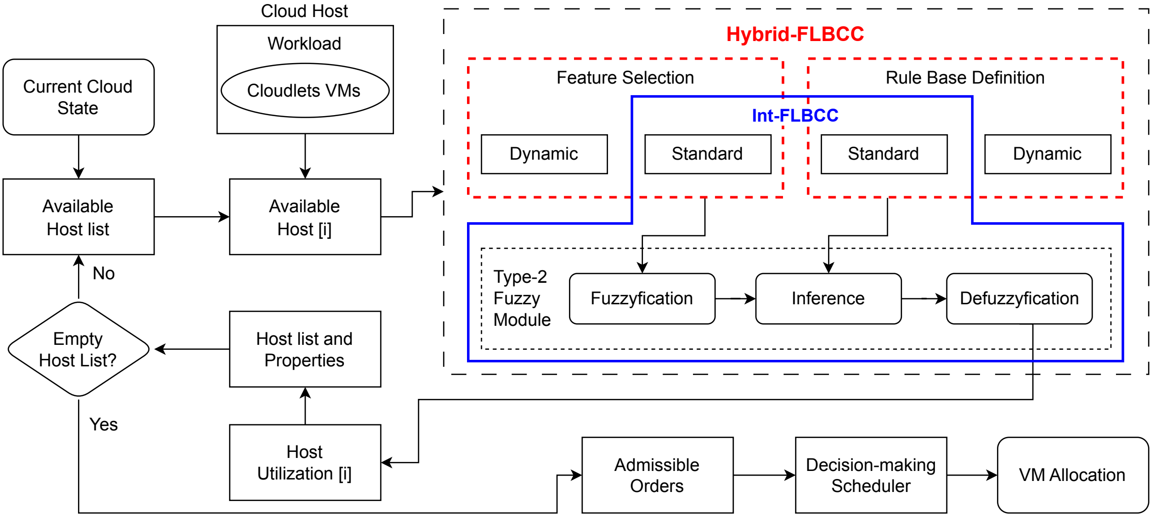

Figure: Overview of the Hybrid-FLBCC Extending the Int-FLBCC Approach.

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Conclusions

- Initial results: Hybrid-FLBCC improves VM consolidation with data-driven fuzzy rules.
- Feature selection enhanced performance and interpretability.
- FURIA provided the most accurate results, with IVTURS as a viable alternative.
- IVTURS extends multi-valued fuzzy approach by incorporating IvFS, enhancing capability to deal with complex uncertainties
- The proposal simplifies system design while reducing computational cost.

Future Research Directions

- Apply Hybrid-FLBCC to real cloud environments and larger datasets.
- Explore hybrid reasoning models combining fuzzy logic and probabilistic methods.
- Investigate auto-tuning mechanisms for adaptive rule generation.

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