Exploratory Data Analysis in Cloud Computing Environments for Server Consolidation via Fuzzy Classification Models

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Abstract: The present work addresses the challenges of flexible resource management in Cloud Computing, emphasizing the critical need for efficient resource utilization. Precisely, we tackle the problem of dynamic server consolidation, supported by the capacity of Fuzzy Logic to deal with uncertainties and imprecisions inherent in cloud environments. In the preprocessing step, we employ a feature selection strategy to perform attribute selection and, better understand the problem. Data classification was performed by fuzzy rule learning approaches. Comparative evaluations of algorithm classification highlight the remarkable accuracy of FURIA, with IVTURS as a close alternative. While FURIA generates 41 rules, indicating a comprehensive model, IVTURS produces only six, introducing an abstract level to model uncertainties as interval-valued fuzzy membership degrees. The study underscores the relevance of parameter adaptation in mapping feature selection and membership functions to achieve optimal performance for flexible algorithms in the Cloud Computing environment. Our results underlie the structure of a fuzzy system adapted to CloudSim, integrating energy optimization and Service Level Agreements assurance through different server consolidation strategies. This research contributes valuable perspectives to decision-making processes in the Cloud Computing environment.

1 INTRODUCTION

The worldwide public Cloud Computing (CC) market is expected to reach an estimated US$ 679 billion in 2024. This estimate encompasses business processes, platforms, infrastructure, software, management, security, and advertising services delivered by public CC services, as storage, bandwidth, or CPU cycles.

In such scenario, one of the main demands of the CC environment is the efficient management of resources. In this point, the energy efficiency is an interesting issue due its importance on different fronts. Additionally, it keep satisfactory Service Level Agreements (SLA) and Quality of Service (QoS) (Beloglazov and Buyya, 2013; He and Buyya, 2023). Minimizing energy consumption satisfying QoS constraints is complex and is part of the research into dynamic Virtual Machine (VM) consolidation, characterized as an NP-Hard problem (Ferdaus et al., 2014).

VM consolidation involves the identification of underloaded and overloaded hosts, selection of VMs for migration, and their allocation to alternative hosts (Mittal et al., 2019). However, this strategy is a complex task as detecting excessive workload and initiating migration cannot quickly respond to sudden and dynamic changes in the environment (Sowrirajan, 2022).

Fuzzy Logic (FL) (Zadeh, 1965) is frequently employed to assist in decision-making processes, addressing uncertainties and inaccuracies in the variables involved in VM consolidation.

In 1975 Sambuc (Sambuc, 1975) presented the concept of an Interval-valued Fuzzy Set (IvFS), and

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other studies were established, taking into account the uncertainty linked to the construction of a precise interval-valued membership function (Bustince et al., 2016).

The ability to make decisions under uncertainties and the tolerance for imprecision of control systems provide the seminal motivation for development of IvFS. More recently, this logical approach has contributed to solutions for complex problems, reasoning models, deduction, and calculation with imperfect information, also integrating techniques from Artificial Intelligence (AI), such as Machine Learning (ML) and Neural Networks (Lughofer, 2022).

In this context, the integration of Computational Intelligence methodologies, especially Machine Learning, becomes opportune to enhance performance in resource allocation and mitigate energy consumption within Cloud Computing.

By integrating concepts of CC and FL, the objective of this work is to stimulate a discussion focused on flexible approaches to model uncertainties associated with data analysis related to relevant attributes of CC environments. These attributes include CPU usage, memory occupancy, bandwidth, and available storage.

This paper is structured as follows. The first section deals with the contextual foundations of the work. Section 2 introduces Cloud Computing challenge and basic concepts of Interval-valued Fuzzy Logic (IvFL) and some Fuzzy Rule-Based Classification Systems (FRBCS). Related work is presented in Section 3. In Section 4, we discuss the details of Exploratory Data Analysis, including obtaining the dataset, feature selection, and the definition of membership functions and rule base. Section 5 describes the experimental evaluation. Finally, section 6 presents conclusions and future work.

2 MAIN CONCEPTS

In this section, we initiates our exploration by addressing the challenges in CC and presenting foundational concepts in IvFL. Additionally, we introduce various FRBCS.

2.1 Cloud Computing

The operational model of Cloud Computing (CC) allows dynamic resource allocation based on demand (Gourisaria et al., 2020). This elasticity facilitates the provision of high-performance computational environments with optimized equipment investments for the end user, aligning costs with resource requests (Nathani et al., 2012)

In 2014, US data centers consumed an estimated 70 billion kilowatt-hours (kWh), constituting about 1.8% of the total electricity consumption in the USA, according to a report by the Natural Resources Defense Council (NRDC) [1] (Shehabi et al., 2016).

Energy consumption is expected to rise by approximately 4% from 2014 to 2023, reaching an estimated 73 billion kWh in 2023 for US data centers. Companies like Google, Microsoft, and Amazon work towards this goal by using renewable energy and investing in on-site green energy generation.

Efficient resource management in CC requires dynamic consolidation of VMs, structured by identifying overloaded and underutilized physical machines, selecting VMs for migration, and allocating them to other physical machines. However, VM migration, aiming to optimize resource usage, is a complex task as it may not promptly respond to sudden dynamic changes in the CC environment.

2.1.1 CloudSim Architecture

The assessment of strategies and algorithms in cloud computing environments requires effective simulation tools. In this context, CloudSim (Calheiros et al., 2011) emerges as a widely employed and esteemed simulation framework, providing researchers with a modular platform for analyzing policies, algorithms, and strategies (Arshad et al., 2022).

The CloudSim architecture is designed to enable a comprehensive and adaptable simulation of CC environments. Key entities include DatacenterBroker, Cloudlet, VM, Host, and Datacenter. It operates across abstraction layers, including hardware, middleware, and user/broker. The CloudSim architecture is shown in Figure 1.

This architecture encompasses crucial modules, such as resource provisioning and scheduling policies. Extensibility is inherent to CloudSim, allowing the addition of modules and policies to meet specific research or simulation requirements. The modular and scalable nature of CloudSim facilitates its application in diverse scenarios, contributing to detailed simulations in cloud computing environments.

Moreover, compared to physical environments, the possibility of experiment repetitions in a controlled manner is one of the main advantages of simulation tools, as CloudSim, integrating the synergistic variation of the different conditions in the system evaluation.

[1] https://www.nrdc.org

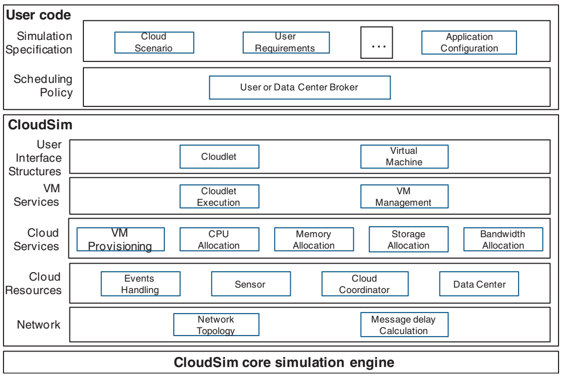

Figure 1: CloudSim architecture (Calheiros et al., 2011).

2.2 Fuzzy Rule-Based Classification Systems

Fuzzy Rule-Based Classification Systems (FRBCSs) represent a potent tool commonly employed to address classification problems. These fuzzy classifiers are renowned for their high classification accuracy and their ability to provide interpretable models through the utilization of linguistic labels (Lucca et al., 2020; Sanz et al., 2021).

The FRBCS consists of two integral components: the Knowledge Base, comprising a specialized Rule Base and Data Base adapted to a specific classification problem, and the Fuzzy Reasoning Method, which is responsible for applying fuzzy logic to the Rule Base and Data Base, managing data uncertainty to effectively assign class labels (Cordón et al., 1998).

The FRBCS design entails a meticulous process involving supervised learning, initiated with a set of correctly classified training examples. The primary objective is to formulate a Classification System capable of minimizing errors in assigning class labels to novel instances. The system's performance is subsequently evaluated comprehensively on test data, providing an approximation of the FRBCS real error. This structured approach underscores the systematic construction and performance assessment intrinsic to FRBCS, substantiating its utility in intricate classification scenarios. Figure 2 shows this process.

This characteristic allows FRBCSs to be applied effectively in various real-world scenarios, spanning industries (Samantaray et al., 2010), healthcare (Czmil, 2023), the economy (Campisi et al., 2022), and numerous other domains. Their wide-ranging application is attributed to their capacity to yield accurate results while ensuring interpretability in the generated models.

The following are examples of FRBCSs employed in this study.

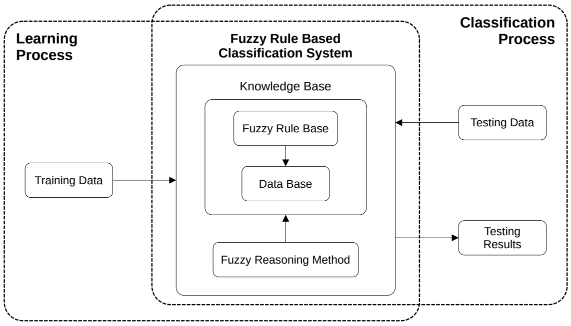

Figure 2: Fuzzy rule-based classification process from training to testing (Cordón et al., 1998).

The FARC-HD (Alcalá-Fdez et al., 2011) algorithm is a computationally efficient solution tailored for high-dimensional challenges, leveraging fuzzy rules and integrating genetic rule selection and parameter tuning to optimize performance. The FARC-HD uses a three-phase strategy that involves acquiring fuzzy association rules through a structured tree approach, meticulous filtering to penalize redundancy, and the integration of a genetic algorithm for rigorous rule refinement. This comprehensive methodology enhances the algorithm's efficacy, making it particularly adept at addressing the nuanced demands inherent in high-dimensional problem spaces.

The Chi-RW algorithm (Cordón et al., 1999) is a classification algorithm discerning the relationship among variables, establishing an association between the resource space and the class space. This algorithm defines linguistic partitions, formulates a fuzzy rule for each example, and assigs the fuzzy region to the highest membership degree. So, linking the label class of an application to the consequence of the rule.

The FURIA (Fuzzy Unordered Rule Induction Algorithm) algorithm is a classification algorithm proposed by (Hühn and Hüllermeier, 2009). In contrast to conventional approaches, this algorithm relies on fuzzy rules to model more flexible classification boundaries. Rules generated by replacing fuzzy intervals use a trapezoidal membership function and a rule induction technique. FURIA generates sets of unordered rules, providing a more flexible representation of patterns in the data.

The IVTURS algorithm (Sanz et al., 2013) (Interval-Valued Fuzzy Reasoning Method with Tuning and Rule Selection) is a FARC-HD extension, incorporating interval-valued fuzzy rules. It employs a parameterized Fuzzy reasoning method and an evolutionary algorithm for optimization, allowing flexible handling of uncertainty in data and effective adaptation to classification problems. IVTURS features a rule selection mechanism to identify the most relevant and significant rules, enhancing computational efficiency and model interpretability.

3 RELATED WORK

This section reports the main projects proposing fuzzy strategies in the stages of dynamic server consolidation in Cloud Computing. The selected papers resulted from a Systematic Literature Review (SLR) realized in (Bastos et al., 2023).

The SLR analysis reveals the dynamic VM consolidation, emerging as an effective strategy to enhance efficiency energy in CC, based on four steps: (i) Overloaded PM Identification; (ii) VM Selection; (iii) Detection of Underutilized PMs; and (iv) Optimized VM Allocation. The underlying goal is to achieve dynamic consolidation of VMs, aiming to optimize the trade-off between performance and energy efficiency.

Table 1 presents an analysis of proposals for resource management in CC, applying techniques on dynamic server consolidation, and highlighting their significance. The description emphasized objectives, logical approach, variables, and prospected tools.

This analysis reveals a pronounced focus on the optimization and minimization of energy consumption in CC environments as a crucial theme to meet the demand for consumption reduction.

Two works stand out for the integration of FL with ML. In (Negi et al., 2021), ML is used to cluster VMs based on resource load. Meanwhile, in (Jumnal and Kumar, 2021), FL is combined with RL to optimize the allocation and/or relocation of VMs. The integration with ML techniques allows FL systems to learn from data, adapting automatically to changes and complexities in the problem. This enables the improvement of fuzzy rules based on the characteristics and relationships present in the data. The other works do not address ML techniques.

Regarding the considered logical approach, only in (Moura et al., 2022) and (Negi et al., 2021) is the multivalued extension of FL considered, specifically IvFL and T2FL, respectively. In (Rozehkhani and Mahan, 2022), Granular Computing is considered. The other works adopt Type-1 Fuzzy Logic.

Regarding the variables considered by Fuzzy systems, it is observed that the assessment of computational power and memory usage is a consensus among the works. In (Negi et al., 2021), (Jumnal and Kumar, 2021), (Braiki and Youssef, 2020), (Mongia and Sharma, 2021), and (Rozehkhani and Mahan, 2022), the authors aim to optimize the allocation or minimize the migration time of VMs. However, they do not account for communication costs, which can lead to bottlenecks in the system when congested, and consequently may lead to unsatisfactory performance.

Another convergence among the works is the use of CloudSim[2] as a simulation tools for CC environments. Thus, our proposed feature selection also considers variables available by CloudSim.

4 METHODOLOGY

In this section, we provide a comprehensive analysis of the considered dataset. The dataset initially comprises variables provided by CloudSim, with the Virtual Machine allocation policy set to Interquartile Range (IQR), and the VM selection policy using Random Selection (RS).

The dataset's foundation lies in workloads sourced from PlanetLab[3]. The collected variables represent the state of each host every 300 seconds, including memory occupancy, CPU usage, bandwidth, available storage, power consumption, and MIPS, along with an indication of the host's utilization level (underutilized, regular, and overutilized).

Regarding the dataset, a feature selection was performed using the Sequential Forward Selection (SFS) (Pudil et al., 1994) technique to eliminate highly correlated variables. The aim is twofold: to enhance overall classification performance and reduce computational efforts involved in processing data. The selection process involves iteratively combining variables to achieve optimal subset configurations based on evaluation criteria.

For this study, we chose the Area Under the ROC Curve (AUC) (Bradley, 1997) as evaluation criteria. This metric was selected strategically to enhance the assessment of the classification performance, providing a comprehensive measure of the trade-off between true positive rates and false positive rates across different classification thresholds. The AUC metric is particularly well-suited for our objectives, as it offers a holistic evaluation of the model's discriminatory capacity, considering various decision thresholds and encompassing a broader understanding of its predictive capabilities.

Thus, in the first iteration of SFS, an individual analysis of variables is conducted, selecting the one with the best classification performance. In the next iteration, this variable is combined with others in search of the combination with the best performance. This process is repeated until there is no further improvement in classification performance.

In this study, the application of SFS considers

[2]http://www.cloudbus.org/cloudsim/
[3]https://planetlab.cs.princeton.edu/

Table 1: Summarized analysis of selected papers in the SRL process.

Strategy	Goal	LA	Variables	Tools
Int-FLBCC	Optimizing energy consumption, reducing SLA violations, and minimizing the number of VM migrations	IvFL	Computational Power; Communication Cost; Memory	■ □
CMODLB	Improving resource utilization, load balancing and energy consumption, reducing task and transmission times	ML T2FL	CPU; Memory; Load Balance in PM	■
FSRL	Reduction of energy usage and resource wastage	FRL	CPU; Memory	■ ▲
Fuzzy-EPO	Minimizing VM migration time and reducing energy consumption	FL	CPU; Memory; Storage; Bandwidth	■
fuzzyBFD	Improving energy consumption and resource utilization	FL	CPU; Memory; Energy; Storage	■
PRSF	Optimizing VM migration for SLA assurance	FL	CPU; Memory	■
GRC model:	Minimizing energy consumption and maximizing QoS stability	GC	CPU; Core Number; Memory; Storage; Service Time; Request Number	■

Logic Approach FL: Fuzzy Logic; IvFL: Interval-valued Fuzzy Logic; ML: Machine Learning; T2FL: Type-2 Fuzzy Logic; FRL: Fuzzy Reinforcement Learning; GC: Granular Computing; ■ CloudSim; □ Juzzy; ▲ Matlab

the KEEL software tool (Triguero et al., 2017), executed with the FARC-HD, FURIA, and IVTURS algorithms.

After feature selection, the resulting combinations were employed as inputs for classification experiments utilizing the FARC-HD, Chi-RW, FURIA, and IVTURS algorithms within the KEEL environment. These experiments also provided parameters, defining the membership function limits and the fuzzy rule base system, and facilitating future adaptations of the fuzzy module on CloudSim.

Details of these experiments, including membership functions and rule bases generated by algorithms, are further elaborated in Section 5.

5 EXPERIMENTAL RESULTS

Comprehending the results of our experiments is crucial for evaluating the effectiveness of the proposed methodology.

In this section, we explore the evolving process of feature selection, evaluate the classification performance of different algorithms, and examine the complexities of their rule generation mechanisms.

5.1 Feature Selection Dynamics

The dynamics of feature selection are presented in Figure 3, illustrating the stepwise contribution of variables in conjunction with the AUC metric for FARC-HD, FURIA, and IVTURS.

5.2 Classification Performance Review

Further insights into the classification performance and optimal variable combinations for each algorithm are detailed in Table 2.

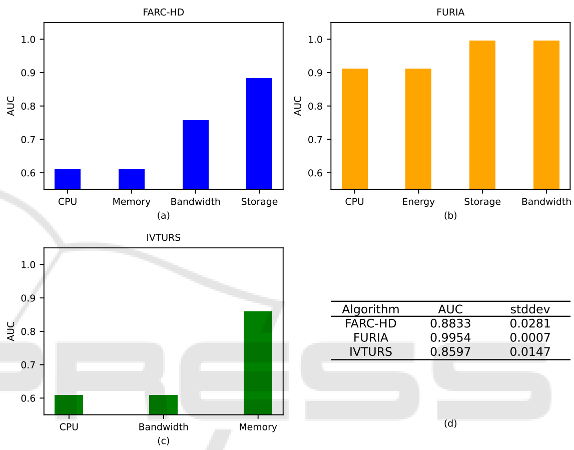

Figure 3: Variables selected by the algorithms: (a) FARC-HD, (b) FURIA, (c) IVTURS, (d) AUC metric evaluation.

The presented results include the mean classification value and standard deviation (stddev) for FARC-HD, Chi-RW, FURIA, and IVTURS.

Table 2: Global Results of Feature Selection Simulation.

Algorithm	Variables	Classification	stddev
FARC-HD	CPU, Memory, Bandwidth, Storage	0.9576	0.0059
Chi-RW	CPU, Memory, Bandwidth, Storage	0.9288	0.0011
FURIA	CPU, Energy, Storage, Bandwidth	0.9970	0.0007
IVTURS	CPU, Energy, Storage, Bandwidth	0.9583	0.0180

5.3 Algorithmic Details

It's worth noting that the FARC-HD, Chi-RW, and FURIA algorithms adopt Type-1 Fuzzy Logic, while IVTURS utilizes interval fuzzy sets, enabling it to handle more complex uncertainties in server consolidation scenarios.

The membership functions corresponding to the optimal variable combinations for each algorithm are outlined in Table 3. Triangular membership functions are predominantly used, with the exception of FURIA, which adopts a trapezoidal format for modeling membership relations. Each variable represents an input of fuzzy system, and is categorized into three linguistic terms: low, medium, and high.

These membership functions are essential for interpreting the output of each algorithm and understanding how variables contribute to the classification process. They provide a linguistic representation of the input variables, allowing for more intuitive and human-understandable analysis.

5.4 Rule Interpretability

The generated rule bases for FARC-HD, Chi-RW, FURIA, and IVTURS consist of 9, 7, 41, and 6 rules, respectively.

We observed a substantial difference in the number of fuzzy rules generated by the algorithms. Notably, FURIA demonstrated a higher complexity, producing an extensive set of 41 rules. While a greater number of rules may imply a more intricate and detailed model, it necessitates careful consideration of the associated computational demands during implementation.

In contrast, IVTURS adopted a more parsimonious approach in fuzzy rule generation, generating a modest total of only 6 rules for data classification. This difference underscores the inherent trade-off between achieving a detailed model and ensuring computational efficiency. Balancing these parameters is essential to optimize the algorithm's application and performance.

The format of rules generated by FARC-HD is based on natural language, where each attribute is associated with a set of linguistic terms describing its characteristics: L_0, L_1, and L_2 represent low, medium, and high, respectively. Each rule consists of a series of antecedent conditions (if-clauses), specifying the relationships between attributes and their respective linguistic terms. The result or predicted class is determined by the conclusion of the rule (then-clause). Additionally, each rule may have a certainty factor (CF), indicating the confidence or certainty in the classification made by the rule.
[(i)] 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
```

Rules generated by Chi-RW follow a similar format to FARC-HD (if-then rules). However, instead of a certainty factor (CF), Chi-RW rules are accompanied by a rule weight, indicating the importance or contribution of the rule to the classification.
[(ii)] Chi-RW 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_normal with Rule Weight: 0.5910
```

Rules generated by FURIA follow a different format, where antecedent conditions are expressed as scalar values for each attribute that lead to the predicted class. The classification result is indicated in the rule conclusion, along with a certainty factor (CF).
[(iii)] 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)
```

Rules generated by IVTURS also follow a format based on natural language, where attributes are associated with linguistic terms. However, IVTURS adopts an interval approach for the certainty factor (CF), instead of associating a single value with each rule. The antecedent conditions of the rules also specify intervals of values for attributes.
[(iv)] 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]
```

6 CONCLUSIONS

In this study, we focused on the dynamic consolidation of servers, a complex activity that involves various aspects such as CPU usage, memory occupancy, bandwidth, storage, and energy consumption. The specific characteristics of CC environment and the defined performance requirements guided the choice of classification algorithms, particularly those based on fuzzy logic.

The Feature Selection highlighted the most relevant variables for server consolidation, resulting in simple fuzzy rule sets and a more direct interpretation. Moreover, this optimized approach simplifies the fuzzy system implementation and may lead to saving computational resources. Feature Selection is a valuable practice to enhance the efficiency and interpretability of fuzzy models, especially in complex scenarios, as addressed in this study.

The comparative evaluation of classification algorithms revealed differences in their performances and approaches. FURIA stood out, demonstrating remarkable precision with a high AUC value of 0.9970, consolidating its effectiveness in classification. IVTURS showed a performance very close, with an AUC of 0.9583, positioning it as a potential alternative.

Table 3: Membership Functions.

Variable	Linguistic Term	Chi-RW 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	-∞	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							-∞	-∞	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	-∞	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]

Along with the algorithms FARC-HD and Chi-RW, FURIA adopts Type-1 Fuzzy Logic. Introducing an abstract level, IVTURS extends the multi-valued fuzzy approach by incorporating IvFS, enhancing the capability to deal with more complex uncertainties in the server consolidation case studies.

The servers' dynamic consolidation is a complex activity that involves various aspects and considerations. Thus, the specific characteristics of the environment and the well-defined performance requirements guide the choice of the ideal algorithm. And, the described results in this work provide a valuable perspective to support decisions regarding resource optimization in CC environments, highlighting the role in modeling uncertainties and inherent imprecise data.

In conclusion, our work provides a valuable perspective for supporting decisions regarding resource optimization in CC environments, emphasizing the role of Fuzzy Logic in modeling uncertainties and inherent imprecise data. The complexities of server consolidation in CC environments necessitate ongoing research and innovation to address emerging challenges and ensure sustainable and efficient cloud services.

6.1 Future Research Directions

While our study contributes into server consolidation using fuzzy logic, several promising avenues for future research emerge. We propose the development of an interval-valued fuzzy system for dynamic server consolidation, aimed at optimizing energy consumption in cloud environments while maintaining a satisfactory SLA.

To achieve this, we will explore a distinct set of variables, deviating from those employed in IvFL-based systems (Moura et al., 2022; Negi et al., 2021). Leveraging the outcomes of our feature selection process, we intend to refine inference modeling, adjust membership functions, and establish rule bases using the computational intelligence provided by FRBCS.

Our intention is to enhance the approximate reasoning of this approach by integrating ML techniques. This involves formulating a strategy for dynamic rule generation, operating in conjunction with the inference stage of the fuzzy system. Additionally, we aim to introduce new configurations for the boundary points defining the membership functions and uncertainty region.

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