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# Fog computing task scheduling

a multi-objective AI-based approach

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## **Abstract**

## Introduction

As the number of devices grows exponentially, the demand for computing resources increases. The traditional cloud computing model is not sufficient to handle the massive amount of data generated by these devices. Fog computing is an alternative model that extends the computing resources to the edge of the network, closer to the devices. This model reduces the latency and bandwidth usage, and improves the overall performance of the system. However, the increasing demand for computing resources also raises concerns about the energy consumption and the environmental impact of fog computing systems.

In this paper, we will propose an AI-based task scheduling algorithm that integrate the use of green energy sources while satisfying the Quality of Service (QoS) requirements of the users.

The rest of this paper is organized as follows. In Chapter 2, we present an overview of the existing research on task scheduling, energy efficiency and AI in the context of fog computing. In Chapter 3, we describe the proposed task scheduling algorithm and the integration of green energy sources. In Chapter 4, we present the experimental results and the performance evaluation of the algorithm. Finally, in Chapter 5, we conclude the paper and discuss the future work.

## Related Work

There are many existing studies and researches on the topics task scheduling, energy efficiency and AI in the context of fog computing. The concept of fog computing was introduced by Cisco in 2012 [1], and since then, many researches have been conducted to improve the performance of fog computing systems and reduce their environmental impact.

## Fog computing

Fog computing is a paradigm that extends cloud computing and services to the edge of the network. [2] and [3] respectively investigate the concepts surrounding fog and its applications in the context of IoT. [4] offers an extensive review of the existing work on fog computing.

## Task Scheduling in Fog Computing

### Genetic Algorithms

The task scheduling problem in fog computing has been widely studied in the literature. Many researchers have proposed different algorithms and techniques to optimize the task scheduling process in fog computing systems. [5] offers an analysis of the existing algorithms while identifying the challenges and research gaps. In [6], the authors propose a task scheduling algorithm based on Swarm Intelligence and Machine Learning. This hybrid approach minimizes the execution time and the makespan and improves the performance of the load balancing scheduling. In [7], an optimization model is proposed for the problem of mapping data stream over fog nodes while considering the load of those nodes and the latency between the sensors and the nodes. A heuristic based on genetic algorithms is then presented to address the complexity of the problem. In [8], the authors propose a task clustering and scheduling mechanism based on Differential Evolution to find the optimal execution time for the tasks. The mechanism is compared to the Firefly Algorithm and Particle Swarm Optimization, and the results show that the proposed mechanism outperforms the other two algorithms in terms of execution time, system efficiency and stability.

### Fuzzy Logic

[9] proposes a ranking-based task scheduling method that combines fuzzy logic and user preferences. In [10], the authors propose an approach based on Fuzzy Logic for real-time task scheduling in IoT applications.

## Energy Efficiency in Fog Computing

The energy efficiency of fog computing systems has been a major concern for researchers. [11] introduces a mathematical framework to evaluate the trade-off of fog computing systems, especially in terms of power consumption and energy efficiency. In [12], the authors propose two Integer Linear Programming models, where the second one aims at minimizing the energy consumption while maximizing successfully provisioned tasks. The authors of [13] provides an overview of the energy efficiency challenges in fog computing and presents a comprehensive survey of the existing energy-efficient techniques and algorithms. An energy-aware Metaheuristic algorithm based on the Harris Hawks Optimization algorithm, itself based on a local search strategy for task scheduling in fog computing, is proposed in [14]. [15] proposes an energy efficient algorithm through an integrated computation model.

## AI in Fog Computing

The use of AI in fog computing has been a growing trend in the literature. An efficient binary CNN with numerous skip connections is proposed by the authors of [16]. In [17], the authors designed an intelligent energy-saving model based on CNN and a task scheduling model is designed based on the policy gradient algorithm. [18] present an improved convolutional neural network so solve the value function of a Continuous Markov Decision Process model, so it can be applied to a multi-user system.

# Offloading using Fuzzy logic

## Introduction

Introduced in 1965 by Lotfi Zadeh[19], fuzzy logic is based on a "degree of truth" instead of a finite value, usually 0 or 1, it aims to represent the vagueness of human language and thought. Fuzzy systems are the means to implement fuzzy logic, they are two types of fuzzy systems: Mamdani and Sugeno, both are similar but differ in the way the output is determined. The most common one Mamdani and it's the one we will be using in this project. The Mamdani fuzzy system follows three steps:

- the inputs are fuzzified into fuzzy membership functions,
- a set of rules are applied to the fuzzy inputs to determine the fuzzy output,
- the fuzzy output is defuzzified to get a crisp value.

## Fuzzification

Fuzzification is the process of converting a crisp value into a fuzzy value, this is done by assigning a membership function to the input value. The membership function is a curve that defines how much the input value belongs to a certain fuzzy set. The most common membership functions are the triangular and trapezoidal functions, they are defined by three or four parameters respectively. The triangular function is defined by the parameters  $a$ ,  $b$  and  $c$  and is given by:

$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a, \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b, \\ \frac{c-x}{c-b} & \text{if } b \leq x \leq c, \\ 0 & \text{if } x \geq c. \end{cases} \quad (1)$$

The trapezoidal function is defined by the parameters  $a$ ,  $b$ ,  $c$  and  $d$  and is given by:

$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a, \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b, \\ 1 & \text{if } b \leq x \leq c, \\ \frac{d-x}{d-c} & \text{if } c \leq x \leq d, \\ 0 & \text{if } x \geq d. \end{cases} \quad (2)$$

## Rule evaluation

The rule evaluation is the process of determining the fuzzy output based on the fuzzy inputs and a set of rules. The rules are defined by two parts: the "if" or antecedent part and the "then" or consequent part. The antecedent part deals with inputs, it can either be a single input or a combination of inputs, the combination can be done using the logical operators "and" and "or". The consequent part deals with the output. In the context of this project, the rules are usually of the form "if Bandwidth is low then processing is local". The rules are generally defined by the user and are based on their knowledge of the system.

## Defuzzification

Defuzzification is the process of converting a fuzzy output into a crisp value, there are several methods to do this, the most common one is the centroid method. The centroid method calculates the center of mass of the fuzzy output, this is done by taking the weighted average of the output values. The weighted average is calculated by taking the sum of the product of the output value and its membership value divided by the sum of the membership values. The formula for the centroid method is given by:

$$y = \frac{\sum_i \mu_i \cdot y_i}{\sum_i \mu_i} \quad (3)$$

Where  $y$  is the crisp output,  $\mu_i$  is the membership value of the output value  $y_i$ . The centroid method is the most common method because it is simple and easy to implement. However, it is not always the best method, other methods like the mean of maximum and the largest of maximum can be used depending on the application.

## Fuzzy system for offloading

To demonstrate the use of fuzzy logic in offloading, we wrote two simple programs in Python. The goal was to recreate the experiment done by Hari et al.[20]. The first program uses the pyfuzzylite[21] library to implement a fuzzy engine with all the variables and rules needed to determine the offloading decision. The second program uses the NumPy library to generate random values for the inputs and then uses the fuzzy engine to determine the offloading decision. The fuzzy engine is defined by the variables shown in table 1 and 2.

Name	Range	Fuzzy set	Membership function	Parameters
Bandwidth (in Mbps)	[0, 100]	bw_low bw_med bw_high	trapezoidal trapezoidal trapezoidal	0, 20, 30, 40 35, 45, 60, 70 65, 75, 90, 100
Data size (in KB)	[0, 600]	data_low data_med data_high	trapezoidal trapezoidal trapezoidal	0, 0, 230, 360 250, 350, 470, 590 450, 540, 600, 600
Residual battery charge (in %)	[0, 100]	bat_low bat_med bat_high	trapezoidal trapezoidal trapezoidal	0, 0, 25, 35 25, 40, 60, 75 60, 75, 100, 100
Load (in %)	[0, 100]	load_low load_med load_high	trapezoidal trapezoidal trapezoidal	0, 0, 25, 40 35, 45, 60, 70 65, 80, 100, 100
Memory (in %)	[0, 100]	mem_low mem_med mem_high	trapezoidal trapezoidal trapezoidal	0, 0, 25, 40 35, 45, 60, 70 65, 80, 100, 100
Virtual machines available	[0, 50]	vm_low vm_med vm_high	trapezoidal trapezoidal trapezoidal	0, 0, 15, 20 15, 22, 37, 40 30, 35, 50, 50
Number of concurrent users	[0, 100]	user_low user_med user_high	trapezoidal trapezoidal trapezoidal	0, 0, 25, 40 30, 40, 60, 70 60, 75, 100, 100

Table 1: Input variables for the fuzzy engine.

Name	Range	Fuzzy set	Membership function	Parameters
Offloading decision	[0, 100]	local remote	trapezoidal trapezoidal	0, 12, 24, 48 36, 60, 72, 100

Table 2: Output variable for the fuzzy engine.



Conclusion

Conclusion

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