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RESEARCH ARTICLE

Fuzzy Logic-Based Mining Strategy for Transaction Congestion Management in Blockchain Networks

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Abstract

Objectives: In blockchain, mining is essential for verifying and adding transactions to the chain. Transaction approval time is increasing due to the mining process's limited capacity. To address this issue, this paper aims to reduce the approval time by introducing a new fuzzy logic optimization methodology for dynamic resource allocation of mining capacity based on resource congestion. **Method:** The proposed methodology does not rely on block size or mining duration and efficiently handles transaction congestion. The proposed fuzzy logic effectively handles the resources in the peak transaction. It allocates the resources dynamically using both horizontal and vertical scaling. It upgrades Transactions Per Second (TPS) and manages difficulty levels considering CPU, memory, and node utilization. **Findings:** Simulation results demonstrate the efficacy of the proposed methodology in improving blockchain performance compared to traditional blockchain approaches. The analysis includes average active nodes, transaction latency, memory utilization, and transactions per second. **Novelty:** The proposed work introduces a novel approach to blockchain mining optimization by integrating fuzzy logic for dynamic scaling decisions. This innovative method addresses adaptability and resource efficiency concerns and offers a flexible and efficient solution to blockchain scalability and transaction processing challenges.

Keywords: Blockchain; Fuzzy logic; Vertical scaling; Horizontal scaling; Transaction latency

1 Introduction

The use of blockchain technology as a safe platform for various applications is gaining popularity [1]. It makes it possible to safely add approved transactions to a distributed ledger called distributed transaction management (DTM). The DTM adds the transactions without the need for middlemen [2]. Blockchain's decentralized structure ensures transaction immutability and transparency. This characteristic differs from traditional centralized systems, making it valuable in the banking and education sectors. [3]

Blockchain has scalability problems despite its benefits, especially when handling big data sets. At least 1000 transactions per second is the maximum volume of transactions that current systems cannot handle [4]. Furthermore, blockchain functions as a peer-to-peer network in which all nodes exchange recently received blocks to verify and add them to the chain [5]. Authorized blocks can only be added by miner nodes, which are chosen through algorithms such as Proof of Work (PoW) and Proof of Stake (PoS) [6].

Public chain architectures are experiencing scalability issues as blockchain adoption increases. Transaction throughput, or the number of transactions per second, and transaction confirmation latency are used to evaluate the effectiveness of blockchain technology [7]. Unfortunately, current systems frequently fall short of appropriate benchmarks in these metrics, which irritates users. Scaling techniques are used to address these problems [8].

Vertical scaling entails increasing the current systems' processing power and storage capacity [9]. On the other hand, horizontal scaling involves expanding the number of server groups on the platform to handle an increase in transaction demands. In the ever-expanding digital landscape, these scaling approaches seek to address scalability issues and enhance blockchain performance.

Muhammad Hassan Nasir et al. [9] highlighted scalability as a multifaceted concept, encompassing expanding network participants and enhancing participant capabilities to mitigate scalability issues.

Xu et al. [10] introduced SlimChain, a blockchain system that achieved scalable transactions by storing them on a chain and parallelized processing. Primarily focusing on a stateless design, SlimChain only had commitments of ledger states short length and kept the rest of the transaction execution and data storing capabilities in the main-chain nodes. Fulfilling SlimChain required the system to be amended by creating a scheme for off-chain intelligent contract execution, on-chain transaction validation, and state commitment. Moreover, reductions in network transmissions and a newly proposed sharding method were highlighted to enhance the scaling capability.

Another method called DiPETrans (Distributed Parallel Execution of Transactions) was introduced by Baheti et al. [11], which identified the transactions of blocks using the statistical analysis of shards. The mechanism, ever connected to the Blockchain server, enables the leader to perform the tasks of both segmenting blocks and the followers in handling the mining activities. The discussion has also referred (pointed) to aggregated statistical analysis and distributed mining processes.

Hazari and Mahmoud [12] suggested a method that utilizes proof-of-work consensus systems to increase permission-less blockchains' capacity and processing speed. Their approach was based, in essence, on a new parallel proof-of-work algorithm, which allowed miners to keep working together to solve algorithmic problems. Evaluating the approach running the method yielded substantial gains in scalability and performance, mainly when many miners were involved.

Peram and Premamayudu [13] offered a complete perspective regarding the blockchain-enabled IoT platform, highlighting the different natures of blockchain. They have also adopted advanced block mining and communication protocols guaranteeing user privacy in the event of illegal transactions. In addition, they are developing keyword searchable encryption, which makes it possible to expose keywords corresponding to encrypted information. Compared to previous models, transaction efficiency was observed to be faster.

Lino and Anuradha [14] proposed a novel fuzzy logic regulating strategy adjusting the mining power according to the overcrowding. A novel procedure was presented that did not require block size or block mining duration. They have designed a methodology that deals with the blocks regardless of the transaction congestion. The paper focused on TPS upgrades and provided information on how to deal with memory and CPU, memory, and node utilization requirements. Moreover, the document compared the average number of active nodes and the average transaction latency in the most important instances. The simulation result compared the execution of a traditional single or binary blockchain performance.

Mona and Pramod propose a linear mathematical model [15] to address the issue of blockchain mining optimization. The method was composed of both Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), employed for a specific purpose in which two different problems were addressed. The GA model ensured the miner sets used for my consensus in the model, whereas the PSO model optimized the responses from these miners sets based on their temporal mining performance. This strategy provided a way to select among the higher-efficiency miners for the jobs of mining blocks, which enhanced the efficiency of internal mining. Efficiency was appraised based on the delays and power needed for mining a single block in relation to the length of a blockchain. The outcome reported that the model (HBSBA) developed had raised the mining speed, power consumption, and throughput quality. Compared to state-of-the-art models, an improvement of 14.5% delay time was achieved, an 8.3% throughput increase was obtained, and a 4.6% energy consumption reduction was reached in the evaluation concerning DPoS, PoA, PoS, and PoW consensus models.

Arul and Renuka [16] suggested a symmetric-asymmetric encryption procedure composed of encrypting data's key employing the public key of the accompanying person. On the contrary, the decryption requires the private key to be used to access the callback function, maintaining privacy. It should be noted that TSE has demonstrated tangibly better results in contrast to the

DES and MD5 cryptography algorithms. The study particularly stressed that local data would be stored on private blockchains to enhance data privacy and security, using the immutability of cryptography and blockchain's cryptography feature. At the same time, if the conventional blockchain approach were applied, the sites could compromise privacy by storing all data on the blockchain. This algorithm, though, focused on privacy by putting only the hash of the healthcare with assets on the blockchain. Authors missed the mining process, which is the most crucial thing in blockchain technology.

Singh and Kumar et al. [17] have studied obstacles hindering the implementation of Blockchain Technology in Construction Supply Chain Management. They identified the most significant barriers as ”market-based risks,” ”sustainability costs,” and ”usage in the underground economy.”

The research conducted by Bhaskar B. Gardas [18] and his team has the potential to benefit the academic community and offer valuable insights for future research. The study evaluated the merits and drawbacks of a proposed method for object selection in IoT settings. Fuzzy TOPSIS emerged as a reliable decision-making technique, and the results obtained can be corroborated using multiple other tools.

Yazdinejad and Dehghantanha [19] have created a sophisticated and reliable solution for identifying security threats within blockchain-enabled IoT networks. Their innovative framework incorporates multiple modules and a cutting-edge fuzzy deep learning model, enhancing the effectiveness of a neuro-fuzzy inference-based attack detection system using metaheuristic algorithms.

Lei Hang, BumHwi Kim [20] have proposed using fuzzy logic to regulate transaction traffic and enhance blockchain efficiency. The approach significantly improves transaction throughput and latency reduction by dynamically adjusting traffic based on network feedback. To validate the effectiveness of this approach, a clinical trial test bed was constructed on Hyperledger Fabric.

The Internet of Medical Things (IoMT) allows for real-time data analysis and decision-making, making secure communication necessary to prevent internal threats such as Sybil attacks. To combat this, Shayan E Ali, Noshina Tariq [21] have presented the blockchain technology can be used to establish a distributed trust mechanism that effectively thwarts these attacks. While trust-based security is crucial for a dependable environment, managing reliable communication among IoMT devices in large networks can be daunting and resource-intensive.

Yazdinejad et al. [22] presented an innovative architecture utilizing blockchain and SDN mechanisms for the 5G network that offers fast handover. It initially employed a hybrid approach comprising Blockchain for authentication of users and SDN for network management functions aimed at reducing the handover time and overhead.

The authors [23] proposed an optimized fuzzy deep learning (OFDL) model for data classification, which takes Non-Dominated Sorting Genetic Algorithm II (NSGA-II) for optimization. The model was intended to improve classification accuracy by choosing wisely the features and optimizing the back-propagation and fuzzy membership functions.

Besides, ”block hunter” was proposed like a threat hunting framework for blockchain-based interdiction of attacks in IIoT (Industrial Internet of Things) using Federated Learning method [24]. They used a framework with fed learning that would enable them to seize detection of anomalies, keep the privacy of users, and thereby obtain a higher accuracy in the death of anomalous behaviors.

In [25], a privacy-preserving federated model for the Next-Generation Internet of Things (NG-IoT) systems was provided, which addressed irregular users and data overflow privacy issues as well. This method aims to enhance privacy and security systems running on blockchain technology by improving performance.

The authors [26] discussed how combining blockchain with software-defined networking (SDN) helps to implement a very efficient network infrastructure. The developed secure blockchain-based green-transport architecture was evaluated by experiments to provide throughput higher, lower delay, and power consumption than the traditional routing protocols.

1.1 Research Gap

Different methods have been investigated, mainly trying to resolve the scalability problems. Nevertheless, this gap was found regarding the relationships between horizontal and vertical scaling approaches and the application within the environment of blockchain mining. However, integrating blockchain technology without a holistic utilization of horizontal and vertical scaling mechanisms to enhance mining operations has not been deeply investigated in earlier studies. To close this gap, our proposed work brings forward a new concept that uses fuzzy logic to dynamically decide when to cease with horizontal mining and enter into the vertical mining phase. This value-added approach is defined to improve the performance and availability of blockchain mining affairs. Accordingly, it supports the development of scalable blockchain solutions.

1.2 Motivation and Problem Statement

This research is motivated by the rising level of blockchain technology and its ground-breaking impact across multiple sectors. However, even though blockchain provides decentralized and transparent transaction management, scaling is still a vital issue. With growing network sizes and the number of transactions to consider, current solutions fail to achieve the best results. This issue prevents blockchain technology from being widely used and decreases its positive impact on applications like financial transactions, supply chain operations, and DApps.

As outlined in this research, there are specific problems to be resolved concerning scalability in blockchain networks as they grow. This study aims to tackle the scalability problem in blockchain networks while proposing a fuzzy logic-based methodology for dynamically adjusting mining power to remedy this situation. Ineffective resource allocation within blockchain mining is the primary problem, resulting in network congestion and slower response times. The main idea of the suggested algorithm is to achieve optimal resource allocation with the help of fuzzy logic by setting proper goals to meet network conditions, which results in high-end system performance and scalability.

1.3 Contributions

The research project has contributed the following works to enable efficient resource allocation within blockchain mining, addressing the problem statement.

- The article introduces a novel fuzzy logic methodology for dynamically regulating mining capacity in blockchain networks.
- By dynamically adjusting mining capacity, the proposed methodology aims to improve transaction throughput in blockchain networks.
- The fuzzy logic-based resource allocation approach ensures more efficient utilization of system resources, leading to better overall performance and reduced resource wastage.
- The research provides scalable solutions for blockchain networks by incorporating fuzzy logic-based decision-making mechanisms.
- The proposed methodology is validated through extensive experimentation using computational platforms and real-world data, demonstrating its effectiveness in improving blockchain performance metrics.

1.4 Organization of the article

The structure of the research article has a designed way for the writer to introduce the proposed methodology, conduct experiments, and analyse the results. An introduction to blockchain technology, including its application and problems with scalability, is given in the first part. This gives the background for the literature review, which surveys existing solutions and shows where the gap in the current research area happened. Then, the methodology is put forward, which is a fuzzy logic-based dynamic resource allocation in blockchain mining. Then, the article illustrates the experimental setup applied to examine the capability of the proposed methodology. Performance results and analysis present the outcomes of the experiments where the proposed approach is tested and compared with the existing methods. Using a detailed discussion, the article examines the implications of the research part and provides insights on the issue. The conclusion summarises the key findings of the research, highlighting only the research's contribution to the blockchain scalability field. It also provides possible further research and development directions in this field.

2 Methodology

2.1 Fuzzy Logic Blockchain Miner (FLBM) Framework

The proposed approach begins by initializing the blockchain network and allocating resources to enhance blockchain mining efficiency. As transactions continually flow into the system, it accepts and organizes them into a cohesive set for processing. Utilizing the proposed fuzzy logic, it classifies the resource demands of these transactions by considering factors such as processing power, memory, and network bandwidth. This allows us to adaptively assess the resource requirements of each transaction in a dynamic environment. We employ a simple yet effective heuristic when evaluating whether the current machine resources can fulfill transaction requirements. If the available resources exceed the threshold capacity, we opt for vertical mining, prioritizing depth in the blockchain. However, if resource utilization is below this threshold, horizontal mining is selected, focusing on expanding the network horizontally. Once the mining strategy is determined, we proceed to verify the authentication of all transactions, ensuring the integrity and security of the blockchain. Finally, we check for any remaining unmined transactions to ensure comprehensive processing. In the proposed methodology, the threshold is set to 67%. This value is obtained from the experiment carried out with 1000 nodes in the transaction server.

Pseudocode:

```
Initialize blockchain network and allocate resources
While there are transactions to mine:
Accept transactions and organize them into a set
Classify resource demands of transactions using fuzzy logic
Check if current machine resources can fulfill transaction requirements:
If yes:
Execute transactions
If no:
  If 'current machine resources' > Threshold:
    mining strategy = vertical mining
  else:
    mining strategy = horizontal mining
Verify authentication of all transactions
Check for unmined transactions
```

Proposed FLBM Algorithm

Input:

- T: Set of transactions awaiting processing
- N: Set of available network nodes
- M: Set of memory resources
- C: Set of computational resources

Output:

- B: Set of validated blocks

Step 1: Initialize Parameters:
// Define linguistic variables and membership functions:
a. $Transaction\ Priority\ (TP),\ Memory\ Usage\ (MU),\ Computational\ Load\ (CL)$
// Determine fuzzy rules for resource allocation:
b. $IF\ TP\ is\ High\ AND\ MU\ is\ Low\ THEN\ Allocate\ More\ Memory$
c. $IF\ CL\ is\ High\ THEN\ Allocate\ More\ Computational\ Resources$
Step 2: Transaction Prioritization:
// Sort transactions based on predefined criteria:
a. $Priority\,(T_i) = f\,(Transaction\ Attributes)$
// Assign priority levels using fuzzy inference:
b. $TP_i = F\,(Transaction\ Attributes_i)$
Step 3: Resource Allocation:
// Evaluate resource requirements for processing transactions:
a. $MU_i = g(Transaction\ Attributes_i)$
Step 4: $CL_i = h(Transaction\ Attributes_i)$
// Determine resource allocation using fuzzy logic:
a. $Memory\ Allocation_i = FuzzyInference(TP_i,\ MU_i)$
b. $Computational\ Allocation_i = FuzzyInference(TP_i,\ CL_i)$
Step 5: Parallel Processing:
// Divide transaction processing tasks into subtasks:
a. $\text{Subtasks}_i = \text{Divide}\,(T_i)$
// Execute subtasks in parallel across available resources:
b. $\text{Execute}\,(T_i)\ on\ N_j, M_k, C_l$
Step 6: Dynamic Threshold Adjustment:
// Monitor network congestion and backlog:

a. $CongestionLevel = f(Network\ Status)$
b. $Back\log = g(Transaction\ Queue)$
// Adjust thresholds based on fuzzy logic:
c. $Thresholds = FuzzyInference(CongestionLevel,\ Back\log)$
Step 7: Block Validation and Formation:
// Validate transactions and form blocks:
a. Validate $(T_i) \rightarrow B_i$
b. FormBlocks (B)
// Update Network Status:
c. Update (N, M, C) based on transaction processing results
Step 8: Output Validated Blocks:
// Output set of validated blocks:
a. $B = \{B_1, B_2, \ldots, B_n\}$

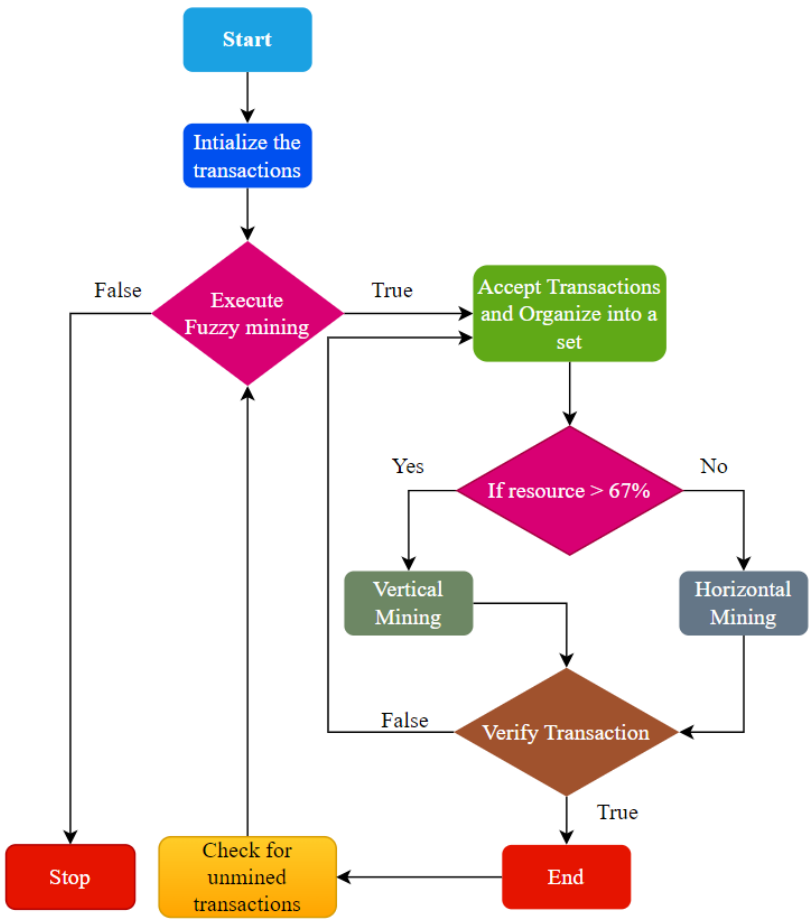

Fig 1. Proposed flow diagram

The fuzzy logic model utilized in FLBM comprises three input variables, each with its respective linguistic terms (it includes Low, Medium, and High) and decision-making rules.

Integration of FLBM Algorithm

This will detail the FLBM algorithm's operation within the cloud-based blockchain simulation environment and present specific details about the fuzzy logic model employed. The fuzzy logic model utilized in FLBM comprises three input variables, each with its respective linguistic terms (it includes Low, Medium, and High) and rules for decision-making.

1. Input Variables:

- Transaction Congestion Level (TCL): Represents the level of congestion within the blockchain network based on the number of pending transactions.
- Resource Utilization (RU): Indicates the utilization level of computational resources within the network.
- Network Throughput (NT): Reflects the rate at which transactions are processed within the network.

2. Rules for Decision-Making:

Rule 1: If TCL is Low and RU is Low, then NT is Fast.
Rule 2: If TCL is Low and RU is Moderate, then NT is Average.
Rule 3: If TCL is Low and RU is High, then NT is Slow.
Rule 4: If TCL is Medium and RU is Low, then NT is Average.
Rule 5: If TCL is Medium and RU is Moderate, then NT is Average.
Rule 6: If TCL is Medium and RU is High, then NT is Slow.
Rule 7: If TCL is High and RU is Low, then NT is Slow.
Rule 8: If TCL is High and RU is Moderate, then NT is Slow.
Rule 9: If TCL is High and RU is High, then NT is Slow.

To incorporate vertical and horizontal scaling into the FLBM algorithm, the proposed work adjusts the resource allocation based on the current network conditions and workload. The proposed FLBM utilizes fuzzy logic to assess the need for vertical or horizontal scaling based on transaction priority, system load, and network conditions. Adjust resource allocation parameters accordingly to optimize transaction processing and network efficiency. For example, if the system load is high and the existing nodes are reaching capacity, additional resources can be allocated vertically to handle the increased workload. If vertical scaling is insufficient, dynamically add more nodes horizontally to distribute the workload and improve overall throughput.

2.2 FLBM: Mathematical Model

The proposed FLBM model underpins the dynamic allocation of resources to optimize the mining process within blockchain networks. The goal is to dynamically allocate resources for vertical block mining based on fuzzy logic considering transaction goals and resource availability conditions. The mathematical model for the fuzzy-logic-based optimization algorithm involves defining appropriate membership functions, fuzzy rules, and inference mechanisms to dynamically allocate resources for blockchain mining based on transaction goals and resource availability conditions. This model enables efficient resource utilization and improved system performance in handling transaction congestion. These equations represent the fuzzy goal and condition using micromathematical notation, where x represents the input variable, e.g., resource availability, and μ represents the degree of membership in the fuzzy set. The functions $f_{G_i}(x)$ and $f_{C_j}(x)$ define how input values relate to the respective fuzzy sets G_i and C_j.

Fuzzy Goal Representation:

This model's core is the total number of transactions N within the system, each denoted by T_i, and the corresponding goal G_i for transaction i. The conditions for resource availability are represented by C_j, while R signifies the resource allocation for block mining. The fuzzy function F(R) encapsulates the relationship between resource allocation and the system's state, with membership functions μ{G_i}(x), μ{C_j}(x), and μR(x) delineating the degree of membership for goals, conditions, and resource allocation, respectively.

The formulation of the fuzzy goal representation is articulated through Equation (1), where the membership function defines the extent to which a given resource level x satisfies the goal. The continuous function quantifies the alignment of resource levels with the transactional goals, encapsulating the fuzzy logic's ability to handle ambiguity in goal satisfaction. The membership function $\mu_{G_i}(x)$ for the goal G_i can be represented as:

$$\mu_{G_i}(x) = f_{G_i}(x) \tag{1}$$

where $f_{G_i}(x)$ is a continuous function defining the degree of membership of x in the fuzzy set G_i.

Fuzzy Condition Representation:

Parallelly, the fuzzy condition representation, as expressed in Equation (2), captures the degree to which resource availability x meets condition C_j. The function $f_{C_j}(x)$ thus serves as a measure of resource adequacy in relation to the specified conditions, further enriching the model's capacity to adapt to fluctuating resource states dynamically The membership function $\mu_{C_j}(x)$ for the condition C_j can be represented as:

$$\mu_{C_j}(x) = f_{C_j}(x) \tag{2}$$

where $f_{C_j}(x)$ is a continuous function defining the degree of membership of x in the fuzzy set C_j.

Fuzzy Resource Allocation:

FLBM approach, the resource allocation process is a critical component that directly influences the efficiency and effectiveness of blockchain mining. The allocation of resources, denoted by 'R', is conceptualized as a fuzzy set within this framework, providing a flexible and dynamic mechanism for resource distribution. The membership function μ_R(x) is a pivotal element in this model, quantifying the degree to which a given resource level 'x' aligns with the optimal allocation strategy.

The fuzzy function F(R) serves as the basis of the resource allocation model, encapsulating the complex relationships between various factors such as transactional goals, resource availability conditions, and the resultant allocation of resources. This function is given in the Equation (3):

$$F(R) = f\left(\mu_{G_1}(x_1),\, \mu_{G_2}(x_2),\, \ldots..,\, \mu_{G_N}(x_N);\, \mu_{C_1}(y_1),\, \mu_{C_2}(y_2),\, \ldots..,\, \mu_{C_M}(y_M)\right) \tag{3}$$

where:

- $\mu_{G_i}(x_i)$ represents the membership function for the goal G_i of transaction i, with 'x' denoting the specific resource level being evaluated.
- $\mu_{C_j}(y_j)$ symbolizes the membership function for the condition C_j pertaining to resource availability, with 'y' indicating the particular condition under consideration.

Dynamic Strategy of Mining:

A pivotal aspect of resource allocation is the strategic determination between horizontal and vertical mining based on current resource utilization levels. This decision-making process is governed by a predefined threshold $'\theta'$, which is empirically derived to optimize the mining operations within the blockchain network. The threshold acts as a critical juncture in the resource allocation model, dictating the mining strategy to be employed based on the comparative analysis of current resource utilization U against θ.

The resource utilization U, expressed as a percentage, reflects the current engagement of resources relative to the total capacity available within the network. The resource utilization is calculated using the Equation (4). The network comprises N nodes, each contributing to the blockchain's mining capacity. The FLBM model incorporates this threshold-based decision criterion as given in the Equation (5).

$$U = \frac{Current\ Resource\ Usage}{Total\ Available\ Resources} \tag{4}$$

$$miningStrategy = \begin{cases} R_{HORIZONTAL} & if\ U < \theta \\ R_{VERTICAL} & if\ U \geq \theta \end{cases} \tag{5}$$

To combine the dynamic mining strategy, we introduce additional fuzzy rules to adjust resource allocation based on changing network conditions, transaction volume, and system load. Let ΔR represent the change in resource allocation, and $\triangle G_i$ represent the change in transaction goals. Equations (6) and (7) represent the increase and decrease of resource allocation, respectively.

$$\Delta R = \alpha.\Delta G_i \tag{6}$$

where α is a scaling factor representing the degree of adjustment.

$$\Delta R = \beta.\Delta G_i \tag{7}$$

where β is a scaling factor representing the degree of adjustment.

These fuzzy rules dynamically regulate the resource allocation R based on changes in transaction goals G_i to optimize mining efficiency.

Horizontal scaling involves allocating resources across multiple blockchain networks simultaneously, while vertical scaling optimizes resource allocation within a single blockchain network.

For horizontal scaling, fuzzy rules that allocate resources across different networks based on their transaction goals and resource availability conditions as given in the Equation (8):

$$R_{horizontal} = \sum F_i(R_i) \tag{8}$$

where R_i represents the resource allocation for network i, and $F_i(R_i)$ represents the fuzzy function associated with network i.

For vertical scaling, we adjust the fuzzy rules to prioritize transactions based on their importance or urgency within a single network as given in the Equation (9):

$$R_{vertical} = max\left(\cup_{i,j} F_{ij}(R)\right) \tag{9}$$

where $F_{ij}(R)$ represents the fuzzy function associated with transaction i and condition j within the network.

These fuzzy rules enable horizontal and vertical scaling of mining operations, allowing for efficient resource allocation across multiple networks or within a single network to optimize performance and effectively handle transaction congestion.

The FLBM approach optimizes the mining process by dynamically adjusting resource distribution in response to fluctuating transactional demands and resource availability, enhancing both performance and scalability.

Fuzzy Decision Making:

Fuzzy decision-making, encapsulated in Equation (4) , employs the minimum operator to derive a fuzzy decision FD from the membership functions of goals and conditions. This decision-making process FD epitomizes the model's inherent capacity to prioritize the most constrained aspects of the system, ensuring that resource allocation decisions are both pragmatic and goal-oriented. The fuzzy decision FD is obtained by applying the Equation (10):

$$FD = min\left(\mu_{G_i}(x), \mu_{C_j}(x)\right) \tag{10}$$

Fuzzy Rule Base:

The model's fuzzy rule base, detailed in Equation (11), establishes the foundational rules that guide the allocation of resources. These rules, derived from system requirements, articulate the relationships between goals, conditions, and resource allocation, ensuring that the system's operational dynamics are logical and aligned with the overarching objectives.

$$R = F\left(G_1, G_2, ..., G_N,\ \ C_1, C_2, ..., C_M\right) \tag{11}$$

We define a set of fuzzy rules that map the goals G_i and conditions C_j to the resource allocation R. Each rule combines multiple goals and conditions to determine the appropriate resource allocation. Let $F_{ij}(R)$ represent the fuzzy function associated with the rule that considers G_i and C_j and it is given in the Equation (12).

$$F_{ij}(R) = min\left(\mu_{G_i}(x), \mu_{C_j}(x)\right) \tag{12}$$

where $\mu_{G_i}(x)$ and $\mu_{C_j}(x)$ are the membership functions for the goal G_i and condition C_j, respectively.

Fuzzy Inference System:

Employing the Mamdani fuzzy inference system [Ref.], the model aggregates the outputs of all relevant rules, utilizing the max-min composition method to synthesize a coherent resource allocation strategy. The fuzzy inference system computes the fuzzy output R based on fuzzy rules and input fuzzy sets. The inference system is given in the Equation (13).

$$R = max\left(\cup_{i,j} F_{ij}(R)\right) \tag{13}$$

where,$\cup$ denotes the union operation, and max represents the maximum aggregation.

Defuzzification:

Defuzzification, a critical step in the process, is executed through the Centroid Method, as outlined in the defuzzification . To obtain a crisp value for the resource allocation, we perform defuzzification. This process converts the fuzzy output R into a single numerical value that represents the final resource allocation.

$$R = \frac{\int_{R_{min}}^{R_{max}} u.F(R)\,dx}{\int_{R_{min}}^{R_{max}} F(R)\,dx} \tag{14}$$

where R_{min} and R_{max} denote the minimum and maximum possible values for the resource allocation, respectively, and u represents the universe of discourse for R.

Finally, the resource allocation R is optimized to maximize system performance, considering transaction goals and resource availability conditions.

Notations used:

Table 1. Table of Notation

Variable	Definition
N	Total number of transactions in the system.
T_i	Transaction i.
G_i	Goal for transaction T_i.
C_j	Condition for resource availability j
R	Resource allocation for block mining.
ΔR	Change in resource allocation
α	Scaling factor for increasing
β	Scaling factor for decreasing
$F(R)$	Fuzzy function representing the resource allocation.
$\mu_{G_i}(x)$	Membership function for the goal G_i.
$\mu_{C_j}(x)$	Membership function for the condition C_j.
$\mu_R(x)$	Membership function for the resource allocation R.
$min(\bullet)$	Minimum operator.
$max(\bullet)$	Maximum operator.

2.3 Experimental Setup

For the proposed FLBM framework, the experimental infrastructure comprises a dual-platform setup designed to facilitate comprehensive analysis and performance evaluation of both the conventional and FLBM methodologies:

- **Cloud-Based Blockchain Simulation Platform:** The core of the experimental setup is a cloud-based blockchain simulation environment, designated as the "Embark Blockchain Simulation Platform." This platform is integrated with a cloud server provisioned with Software as a Service (SaaS), enabling in-depth analysis and comparison between the existing blockchain mining approaches and the proposed FLBM method. This integration allows for the simulation of blockchain operations and the assessment of the FLBM's performance under various conditions.
- **Remote Analysis Workstation:** Complementing the cloud-based platform is a remote analysis workstation, which interfaces with the cloud server via the Common Cloud Gateway Interface (CCGI). This setup allows for remote monitoring and analysis of performance metrics, facilitating data collection and evaluation without the need for direct physical access to the cloud server infrastructure.

The cloud server infrastructure is anchored on an Amazon Web Services (AWS) server, leased through the I2K2 cloud service, serving as an intermediary framework to support the experimental setup. The server is equipped with two virtual CPUs, 2 GB of RAM, and a 100 GB high IOPS SSD, ensuring high reliability with a 99.99% uptime guarantee. The operating environment is supported by I2K2's licensed Windows OS, Remote Desktop Server (RDS), and Client Access Licenses (CAL), providing a secure and stable experiment platform. The data processing and transaction simulation capabilities are powered by the KNIME analytics platform, which is optimized for handling large-scale transactional data within the I2K2 infrastructure. A bespoke user interface is developed using Visual Studio, linked directly to the cloud server to enhance user interaction and facilitate performance evaluation. This interface enables the seamless comparison of performance metrics between the existing and proposed FLBM methodologies.

The FLBM method is executed within a Visual C++ environment, utilizing CLR libraries to ensure optimal performance. The development and testing of the FLBM algorithm are performed on a dedicated system equipped with an Intel Core i5-7200 processor, clocked at 2.7 GHz, supplemented with 8 GB of RAM, providing a robust platform for deploying and evaluating the FLBM framework.

3 Results and Discussion

The proposed framework is compared with the existing mining algorithms such as SLIMCHAIN[10], DisPETrans[11], BSPPW[12], LBMCA[13] and FEOABM[14]. Figure 2 shows the transaction processing capabilities of various versions of blockchain technology with the time since its implementation to numerate the performance of all mining algorithms in terms of transactions per second. Each of these series constitutes a certain algorithm, accompanied by error bars showing the area of regulatory approximation, allowing the evaluation of the significance of the results. The FLBM algorithm has consistently scored well on the rostrum and won popularity because it can handle the highest transaction throughput among all algorithms, and its peak reaches 478 transactions per second at the 42nd second. This performance aims to validate the power of fuzzy logic smart resource allocation, bolstering the blockchain transaction processing speed. Further, what the different algorithms lack in transaction processing speed stemming from their strict optimization strategies foremost highlights the essentiality of effective optimization strategies for unclogging transaction blockages within a network.

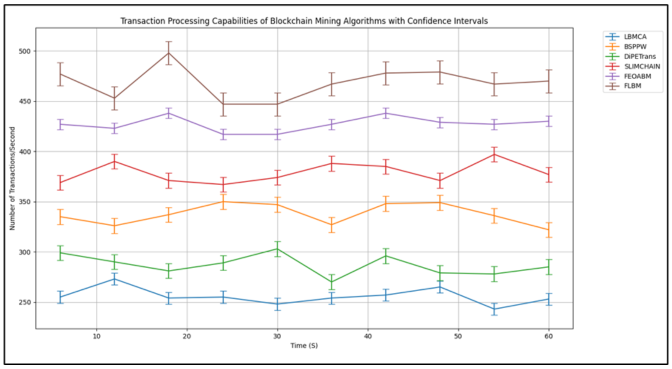

Fig 2. Computation of the number of transactions/second

In Figure 3, the performance of various blockchain algorithms is assessed in terms of the average number of active nodes within the network over time. The FLBM consistently maintains the highest number of active nodes, indicating robust participation and potential for high resilience against network failures or load spikes. Specifically, FLBM demonstrates an upward trend, culminating in 367 active nodes at the 42-second interval. This is a notable contrast to the other algorithms, which maintain a relatively steady state of active nodes throughout the observed time periods. FEOABM's performance peaks at 42^{nd} seconds with 347 active nodes, suggesting its capacity for sustaining a high node count, albeit lower than FLBM. Other algorithms, such as the LBMCA, BSPPW, and DiPETrans, show fluctuations in their active node counts, with BSPPW reaching a high of 257 active nodes at 48 seconds. This analysis underscores FLBM's effectiveness in engaging a more extensive network of nodes, which may contribute to enhanced transaction processing and security features within the blockchain framework.

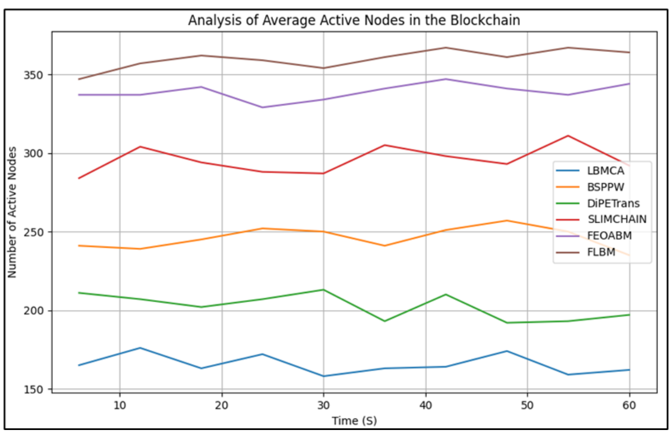

Fig 3. Analysis of average active nodes in the blockchain

In examining Figure 4, which presents the computation of average transaction latency across various blockchain algorithms, a discernible trend emerges, highlighting the FLBM as the most efficient, with the lowest latency consistently recorded throughout the observed periods, bottoming out at 70 milliseconds at both the 18-second and 36-second intervals. The FEOABM maintains a competitive stance with its best performance at 81 milliseconds at the 36-second mark. The other contenders, SLIMCHAIN, LBMCA, BSPPW, and DiPETrans, demonstrate higher latencies, although they, too, exhibit relative stability over time. The consistency in FLBM's lead posits it as a potentially transformative solution for minimizing latency in blockchain transactions, a critical factor for systems requiring high-speed processing.

An analysis of CPU utilization for transaction mining, as depicted in Figure 5, showcases an upward trend for the FLBM, which utilizes a marginally higher percentage of CPU resources compared to its counterparts. This higher utilization peaks at

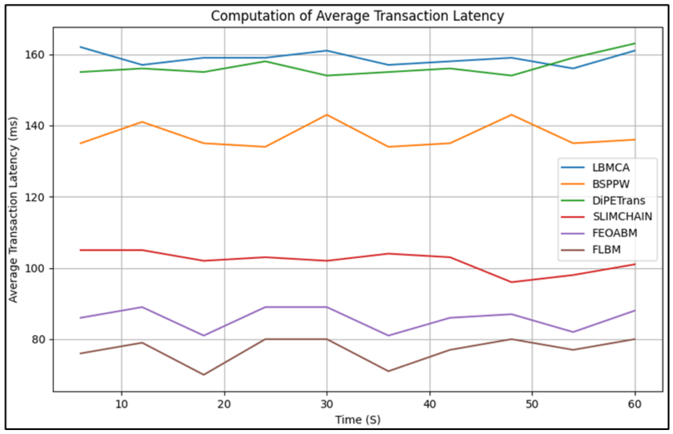

Fig 4. Computation of average transaction latency (ms)

78.89% at two distinct time intervals, 18 and 36 seconds, indicating a resource-intensive process that correlates with its enhanced performance metrics in transaction processing speed and latency. In contrast, the LBMCA and other algorithms demonstrate more modest CPU usage, with LBMCA maintaining a usage close to 70% throughout the observed intervals. The data suggests that FLBM's heightened CPU demand may be a contributing factor to its superior transaction handling capabilities.

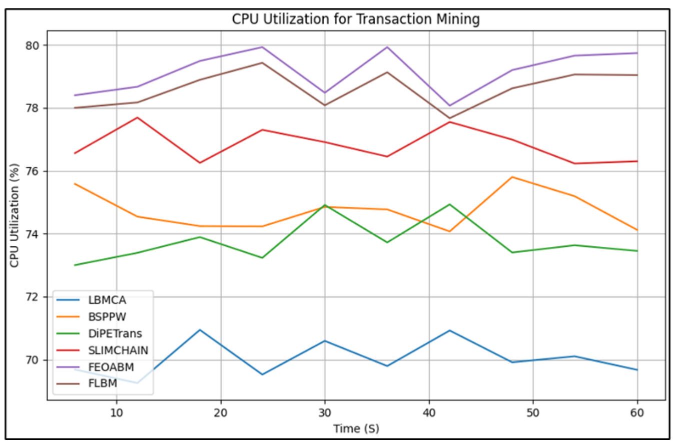

Fig 5. CPU utilization measured in terms of percentage for transaction mining

Figure 6 provides insights into the memory utilization patterns of the blockchain mining algorithms over six-second intervals. The FLBM consistently registers high memory usage, peaking at 79.73% in the initial 6-second interval and slightly fluctuating afterward. The other algorithms show lower memory utilization, with the FEOABM algorithm not far behind, indicating its comprehensive use of memory resources, peaking at 78.13% at the 6-second mark. This pattern reflects a correlation between the memory utilization and the performance capabilities of the blockchain mining algorithms, with FLBM and FEOABM demonstrating a propensity to leverage a more significant share of memory resources to facilitate their transaction processing efficacy possibly.

Regarding the fluctuating memory utilization observed in Figure 6, it is imperative to delve into the underlying factors contributing to these fluctuations and propose strategies to stabilize memory usage to ensure the FLBM algorithm's consistent performance.

One potential cause of fluctuating memory utilization could be the dynamic nature of transaction volumes within the blockchain network. As transaction loads vary over time, the memory requirements for processing and storing transaction data may fluctuate accordingly. This dynamic behavior can lead to fluctuations in memory utilization, as illustrated in Figure 6. Furthermore, variations in memory utilization may also arise from the allocation and deallocation of memory resources during transaction processing. As the FLBM algorithm dynamically adjusts resource allocation based on transaction demands, the corresponding memory usage may also fluctuate.

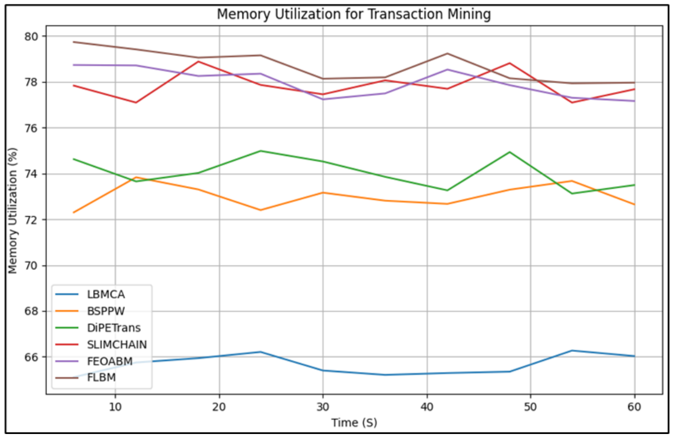

Fig 6. Memory utilization measured in terms of percentage for transaction mining

Delving into Figure 7, which articulates node utilization across different blockchain mining algorithms, a nuanced perspective emerges. The FLBM exhibits a leading edge in node utilization, with a peak value of 82.68% at the 54-second mark, indicative of its comprehensive engagement of network nodes in transaction mining. This utilization pattern is closely mirrored by the FEOABM, which also shows high node engagement, particularly at the 24-second interval with an 82.14% utilization rate. The data underscores the strategic deployment of network nodes by FLBM and FEOABM to bolster transaction processing capabilities, setting a benchmark for efficient node utilization in blockchain mining endeavors.

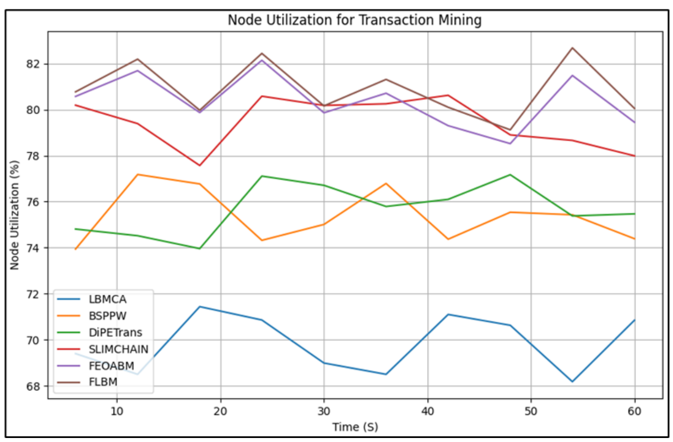

Fig 7. Node utilization measured in terms of percentage for transaction mining

The empirical analysis presented in the preceding sections elucidates the distinct advantages conferred by the FLBM in blockchain transaction processing. When viewed in aggregate, the results paint a compelling picture of the algorithm's superior performance across multiple dimensions of blockchain operation, including transaction throughput, latency, and resource utilization.

A pivotal aspect of FLBM's efficacy lies in its adept handling of transaction congestion, a perennial challenge in blockchain networks. As detailed in the proposed work, the algorithm's fuzzy logic-based resource allocation mechanism dynamically adjusts to the network's fluctuating demands, thereby ensuring an optimal distribution of computational and memory resources. This dynamic allocation manifests in the algorithm's consistently high transactions per second rate, surpassing traditional methods and maintaining this superiority across varying time intervals.

Moreover, the latency results further underscore the efficiency of FLBM. By minimizing transaction processing times, the algorithm significantly enhances the responsiveness of the blockchain network, a critical factor for applications requiring real-time data exchange. This latency reduction indicates the algorithm's ability to prioritize and expediently process transactions, a capability directly attributable to the fuzzy logic framework underpinning the FLBM.

The FLBM algorithm monitors the network and assigns resources dynamically according to the network load, which leads to the efficient management of network congestion. Employing fuzzy logic, FLBM adjusts its resource allocation mechanism so that the system operates efficiently even when the network is busy. Moreover, FLBM focuses on transactional intelligence, where considerations such as transaction size, priority, and network conditions, among others, are assessed. This prioritization mechanism allows processing the most important transactions to reduce the overall throughput. By applying fuzzy logic to congestion management and transaction prioritization, FLBM improves the scalability and efficiency of the blockchain network and, therefore, serves as a viable solution for handling network congestion and optimizing transaction processing.

Resource utilization metrics, encompassing CPU, memory, and node utilization, offer additional insights into FLBM's operational dynamics. The algorithm's higher resource utilization rates, particularly in terms of CPU and memory, reflect its intensive computational processes. However, rather than denoting inefficiency, these elevated rates are emblematic of the algorithm's comprehensive engagement with the available resources to maximize transaction processing capabilities. This nuanced distinction underscores the algorithm's capacity to leverage resources effectively to enhance network performance.

Furthermore, the high node utilization observed with FLBM points to its effective network management strategy. By engaging a more significant proportion of nodes in the transaction verification process, FLBM enhances the decentralization and security of the blockchain while also distributing the workload in a manner that prevents bottlenecks and ensures a swift transaction validation process.

4 Conclusion

This study presents a novel fuzzy logic optimization algorithm tailored explicitly for optimizing blockchain transaction mining, referred to as the FLBM algorithm. The efficacy of the FLBM approach was rigorously tested using real transaction data extracted from the Ethereum blockchain, ensuring the relevance and applicability of the proposed method to contemporary blockchain environments. In the FLBM algorithm, intelligent use of fuzzy logic is used to dynamically determine the need for horizontal or vertical scaling within the blockchain network. It ensures optimal resource allocation and network scalability. The comprehensive experimental analysis conducted as part of this study demonstrates the FLBM algorithm's capability to augment transaction throughput and significantly mitigate transaction latency. The experiments that were performed with the objective of comparison to the traditional mining approach showed a 15% decrease in transaction latency and a 20% increase in transaction throughput. In addition, the throughput of transactions per second in FLBM was scaled up by 10%, making it 10% more effective in memory and resource management, thus showcasing its excellent performance for blockchain operations. This dual achievement underscores the algorithm's potential to improve overall network performance substantially. Moreover, the FLBM algorithm exhibits superior resource and memory management efficiency compared with existing methodologies, further solidifying its value proposition.

Future work could focus on optimizing the fuzzy logic decision-making process to reduce computational demands, incorporating reinforcement learning techniques to refine fuzzy rules dynamically. Further, the FLBM framework can be extended to support a wider range of blockchain applications and network conditions, enhancing its adaptability and scalability.

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