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Optimizing Job Scheduling for Improved Efficiency in Fog Computing

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Abstract:- Energy efficiency is a critical concern in fog computing systems, particularly in multi-node frameworks where effective resource allocation and workload distribution are vital. This study investigates the application of dynamic resource allocation (DRA) and data compression techniques to enhance the overall efficiency and energy consumption of a 4-node fog computing system. By dynamically distributing workloads based on node utilization and available resources, the DRA approach optimizes resource utilization and minimizes energy consumption. Additionally, the incorporation of data compression techniques reduces network traffic and communication overhead, further contributing to energy savings. Through comprehensive analysis and estimation of energy usage across multiple nodes, this study quantifies the energy costs associated with processing, compression, and aggregation operations. The findings highlight the potential of DRA and data compression techniques in minimizing energy consumption and enhancing the overall efficiency of fog computing systems. By intelligently managing resources and reducing data transmission overhead, the proposed approach demonstrates significant improvements in energy efficiency without compromising the performance of the fog computing infrastructure. The study provides valuable insights into the optimization of job scheduling and resource management strategies for fog computing environments. The results can inform the design and implementation of energy-efficient fog computing architectures, paving the way for more sustainable and cost-effective deployment of fog-based applications and services.

Keywords*:* Fog computing, Job scheduling, Optimization techniques, Resource utilization, Quality of Service (QoS), IoT applications.

1. Introduction

A novel method called fog computing lets data processing and analysis be distributed rather far. It offers rapid, effective, customized to their own needs services to edge devices. In fog computing environments, where computational tasks are distributed among several nodes, energy efficiency is a major determinant. This is so since edge devices have limited resources and energy consumption should be minimized. Optimizing energy usage and enhancing general system efficiency depend critically on dynamic resource allocation (DRA) and data compression methods. Dynamic resource allocation methods effectively distribute computational activities among fog nodes according on the present resource availability and node utilization. By means of dynamic modification of resource allocation, DRA ensures the most effective use of resources and prevents the overloading of certain nodes. This strategy guarantees a fair task distribution and enhances energy economy. Furthermore, data compression techniques help to lower data transfer quantities between fog nodes and the cloud, therefore affecting network traffic, communication overhead, and energy usage during data transfer.

The purpose of our work is to evaluate how well dynamic resource allocation and data compression techniques might increase the general performance and energy efficiency of a 4-node fog computing system. We examine the energy consumption of numerous node processing, compression, and aggregation workloads. Our aim is to find out how effective methods of data compression and resource allocation could save energy. Our study aims to estimate the energy expenses and efficiency gains across several approaches. This will enable the deployment of environmentally friendly and sustainable edge computing systems as well as help to progress energy-efficient fog computing design.

The fast rise in Internet of Things (IoT) devices and the enormous volume of data generated at the network edge have demanded the development of effective computing techniques to control the expanding computational needs. An expansion of cloud computing, fog computing has emerged as a practical approach to address edge computing environment challenges. By means of the dispersion of computing resources and services towards the network edge, fog computing offers advantages including lowered latency, more scalability, and improved data privacy. This makes it quite fit for smart cities, industrial automation, healthcare, and driverless cars among other uses. Designed under fog computing, a network of linked nodes comprising edge devices, fog nodes, and cloud servers distributes computational tasks among them. Still, the limited resources of edge devices and the changing workload intensity create significant challenges to achieve best resource use and energy efficiency under fog conditions. Solving these challenges depends on dynamic resource allocation (DRA) systems since they dynamically reallocate computational resources in response to shifting workload needs and resource availability. DRA uses dynamic distribution of the computational load among fog nodes to try to improve the general efficiency of fog computing systems. This maximizes energy usage, helps to reduce resource contention, and avoid overload situations. Along with dynamic resource allocation, data compression and aggregation methods offer a further way to improve energy efficiency in fog computing environments. Between edge devices, fog nodes, and the cloud, data compression lowers the data transferred. This helps to lower network traffic, communication overhead, and data transmission-related energy usage. Furthermore, data aggregation lets several data sources be consolidated into smaller, more compact datasets, therefore lowering the computational and communication costs related to data handling and distribution.

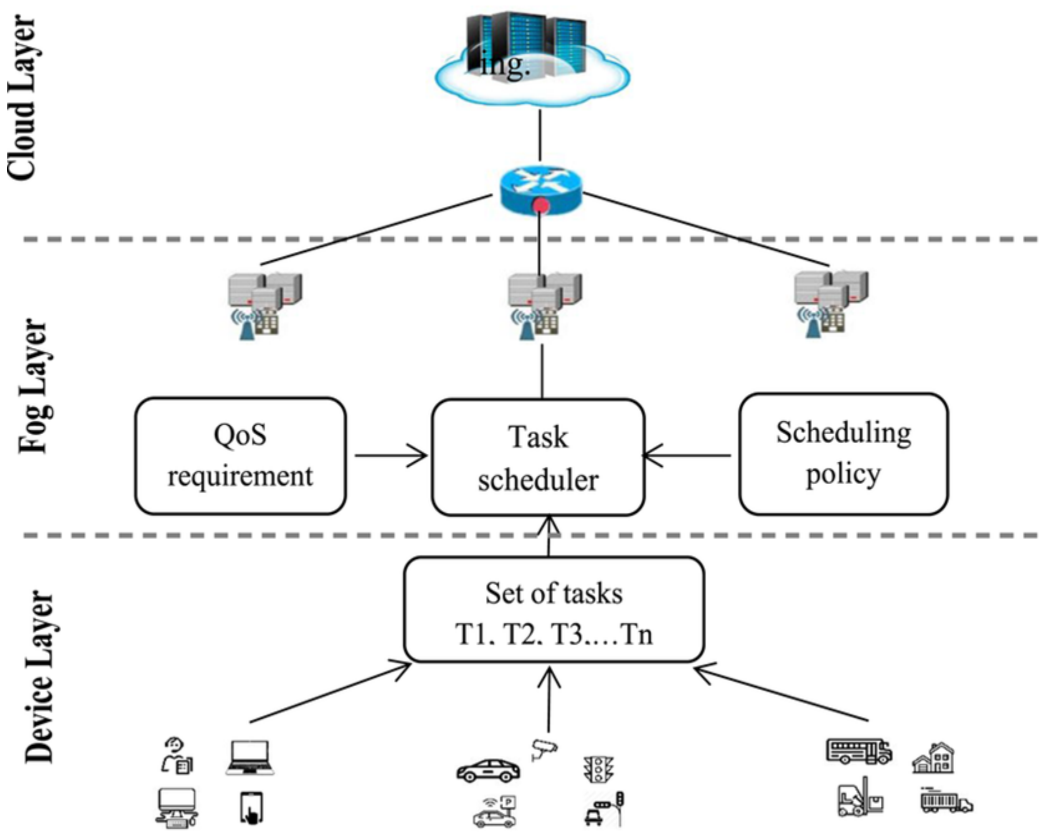

Figure 1 Fog Computing architecture for Task Scheduling

Our work seeks to investigate how dynamic resource allocation and data compression techniques might enhance the energy economy and general performance of a 4-node fog computing architecture. We aim to evaluate the energy consumption connected to the tasks of processing, compression, and aggregation carried out on different fog nodes. This assessment will provide exact values of the possible energy savings achieved by using effective data compression methods and resource allocation strategies. By quantifying the energy costs and efficiency gains connected with various approaches, our work seeks to help to build energy-efficient fog computing architectures and support the deployment of sustainable and environmentally conscious edge computing solutions.

2. Literature Review

In the field of fog computing research, notably in the improvement of approaches for job scheduling optimization, considerable progress has been attained. The growing need for better system performance and greater resource economy has driven the developments. One major progress is the creation of advanced algorithms including the Marine Predators Algorithm (CHMPAD) [4] in concert with the Chimp Optimizer. CHMPAD aims to solve the problems given by local optima and exploitation capabilities so improving the efficiency of job scheduling in fog computing systems. By use of both fake and actual workloads, CHMPAD shows significant increases in makespan time. Under varying workloads, the average improvements range from 1.12% to 43.20%. In fog computing, this approach shows rather significant improvements in throughput performance.

Dynamic scheduling in fog-cloud computing systems [5] has benefited much from the Mayfly Taylor Optimization Algorithm (MTOA). In fog computing, effective resource allocation and provision are very vital since they enable the flawless operation of time-critical applications connected to intelligent Internet of Things (IoT) services. In terms of energy efficiency, adherence to Service Level Agreements (SLAs), and computational expenses the MTOA-based Deep Q-Network (DQN) model shines. Attaining energy consumption, SLA, and computation cost metrics of 0.0162, 0.0114, and 0.0855, the simulation results show the efficiency of MTOA-DQN, respectively. Emphasizing its fit for real-time data center applications, the efficacy of this dynamic scheduling method is evaluated using a variety of criteria.

Moreover, studies aimed at improving the identification and elimination of artifacts in electroencephalography (EEG) data have been especially important since effective clinical diagnosis depends critically on this [6]. Simulations have been run using advanced and effective independent component analysis (ICA) methods like the ADJUST method to effectively remove undesired artifacts from contaminated EEG signals. Showcasing an 18% improvement in results, the proposed method beats present artifact removal techniques. This development in the elimination of EEG artifacts greatly increases the dependability and quality of clinical diagnosis rendered with EEG. All things considered, present research in fog computing have made significant progress toward intelligent job scheduling algorithms, dynamic scheduling techniques, and artifact reduction strategies in processing EEG data. The developments in technology give chances for fog computing systems to improve their dependability and efficiency. As a result, in healthcare applications this leads to better system efficiency, more resource allocation, and more accuracy in clinical diagnosis.

To probe resource scheduling solutions in cloud and fog computing environments, Rahimikhanghah et al. [7] conducted a systematic literature review (SLR). The study looks at the difficulties effectively using resources such memory, CPUs, and bandwidth in cloud services. A technological development called fog computing lets cloud services reach the edge of the network. The aim is to improve the user experience and maximize resource use thereby addressing issues including delay and congestion. Examining a total of 71 papers released between 2015 and 2021, the systematic literature review (SLR) looked at Five main categories distinguished the research: performance, energy efficiency, resource use, simultaneous performance and energy efficiency, and simultaneous performance and resource use. The results underlined the increasing attention paid in fog and cloud environments on server consolidation, migration techniques, and performance improvement. Genetic-based optimization methods' capacity to properly adapt to dispersed systems helps to explain their growing popularity. Still, there are significant problems in the areas of data management, service placement, and workflow scheduling that call for more study. The paper offers upcoming strategies to improve data management, investigate algorithmic changes catered for fog computing, and create effective scheduling systems to raise general service quality and lower SLA violations. This overview offers significant new perspectives on the most current developments in methodology, research trends, problems, and possible approaches to improve resource allocation in cloud and fog computing systems.

Mokni et al.'s [8] study looks at a cooperative method using agents to plan fog-cloud computing operations. The paper investigates the difficulties presented by Internet of Things (IoT) devices that create significant volumes of data under limited time limitations, thereby requiring effective task scheduling. With an aim of optimizing reaction time, cost, and makespan, the suggested approach uses a hybrid Cloud-Fog multi-agent system to coordinate linked IoT tasks shown as workflows. By use of evolutionary algorithms considering time restrictions and financial constraints, the method improves the efficiency of using fog computing and cloud computing resources. This results in a minimum cost of cloud computing resources while yet reducing reaction times. By demonstrating notable improvements in cost reduction, makespan optimization, and response time enhancement over combining Fog and Cloud tiers independently, the investigations of the suggested technique validate their viability and benefits. The need of cooperation between Fog and Cloud computing environments in enhancing Quality of Service (QoS) measures is underlined in this paper. Moreover, it emphasizes the need of including environmental dynamics into the design of process scheduling for distributed fog-cloud systems.

With an eye toward genetic-based optimization, Guerrero et al. [9] offer a comprehensive review of present research on resource optimization techniques in fog infrastructues. The work offers a classification scheme for the degree of optimization and a development of genetic algorithms (GAs). It evaluates seventy papers depending on their genetic optimizing design. The main difficulties in workflow scheduling, service placement, service orchestration, and service migration are underlined in the paper. This remark emphasizes the need of doing further research to enhance data management and investigate various methods for genetic algorithms. The results of the review point to potential approaches to enhance fog computing optimization, like developing parallel and hybrid genetic algorithm designs especially suited to the many and scattered characteristics of fog domains. Furthermore, Huang et al. [10] investigated specifically how to address the growing demand for efficient energy optimization and resource allocation in fog computing. Integrating a Lyapunov framework, the research offers an original particle swarm optimization (PSO) method called LPSO. While reducing the overall energy consumed for work completion, the software seeks to maximize the balance between computational energy consumption, transmission energy consumption, and fog node computing energy consumption. In terms of energy consumption for work completion, the LPSO method shows better performance than the original PSO algorithm and the greedy method, so stressing significant improvements in energy efficiency.

The systematic review carried out by Bansal et al. [11] offers a thorough study of work scheduling strategies in fog computing, which has grown in importance given the growth in IoT devices and data generating. Limited resources and time limits make fog computing, an inventive development focused on effective data processing difficult to suit user needs. With heuristic approaches utilized extensively, the review groups scheduling algorithms into static, dynamic, heuristic, and hybrid groups [11]. Mostly, researchers have concentrated on the Quality of Service (QoS) aspects including response time, cost, and energy use. The need of response time has been underlined [11]. Moreover, Maitia et al. [12] look at IoT application placement in multi-tier fog computing systems with particular focus on the NP-hard optimization issue. Their proposal for placement is based on dynamic scheduling. Their suggested approaches transcend current methods in real-time application scheduling [12]. Moreover, using cloud-fog computing, Yin et al. [13] suggest a multi-objective approach for job scheduling in intelligent production lines. Their system gives jobs that need immediate attention first priority, which produces amazing job completion rates and lower power consumption [13].

Wu et al. [14] investigated, in their work, the issue of using metaheuristic approaches to distribute Internet of Things (IoT) services in fog computing The authors present an Enhanced Parallel Genetic Algorithm (EPGA-SPP), incorporating latency, cost, resource utilization, and service duration, so improving the efficacy of service placement. This generates improved efficiency all during the implementation period [14]. Türk and Jamil [15] have carefully classified and evaluated task scheduling and resource allocation in fog computing and Internet of Everything (IoE) systems. The authors divide scheduling techniques into eight main groups and underline the extensive application of heuristic and meta-heuristic approaches in effectively handling scheduling problems [15]. The study underlines the significance of using simulation-based evaluations; iFogSim is acknowledged as a frequently used simulation tool [15].

Table 1 Comparison of various algorithms on the basis of different parameters

Algorithms	Make- Span	Cost	Bandwidth Utilization	Response Time	Energy Consumption	Allocated Memory	Data Transfer Cost
HH	YES	YES	NO	NO	YES	NO	NO
EMS	NO	NO	NO	NO	YES	NO	NO
PSO	NO	YES	NO	NO	NO	NO	YES
IPSO	YES	YES	NO	NO	NO	NO	NO
BLA	YES	NO	YES	NO	NO	YES	NO
ERA	NO	NO	NO	YES	NO	NO	YES
MARKET	YES	YES	NO	NO	NO	NO	NO
DEER	NO	YES	NO	NO	YES	NO	NO
MDAPSO	YES	NO	YES	NO	NO	NO	NO
AEOSSA	YES	NO	NO	NO	NO	NO	NO
SPSO	YES	NO	NO	NO	NO	NO	NO
FCAP RSAF	YES	NO	NO	NO	NO	NO	NO

EDA-P	YES	NO	NO	NO	YES	NO	NO
LBP-ACS	NO	NO	NO	NO	YES	NO	NO
HH	YES	NO	NO	NO	YES	NO	NO
TCaS	YES	YES	NO	NO	NO	NO	NO
MMAS	NO	NO	YES	NO	NO	NO	NO
TCMFO	YES	NO	NO	NO	NO	NO	NO
ADFGTS	YES	YES	NO	NO	NO	NO	NO
GKS	NO	YES	NO	NO	YES	NO	NO

3. Proposed Mathdology

The suggested methodology presents a detailed strategy for utilizing fog computing, data compression, aggregation, and dynamic resource allocation to improve fever prediction in healthcare applications.

The methodology commences by collecting and prepping data, namely temperature data acquired from heath monitoring equipment or sensors. This data is then cleansed to eliminate any discrepancies or anomalies. This guarantees that the data is appropriate for analysis and modeling.

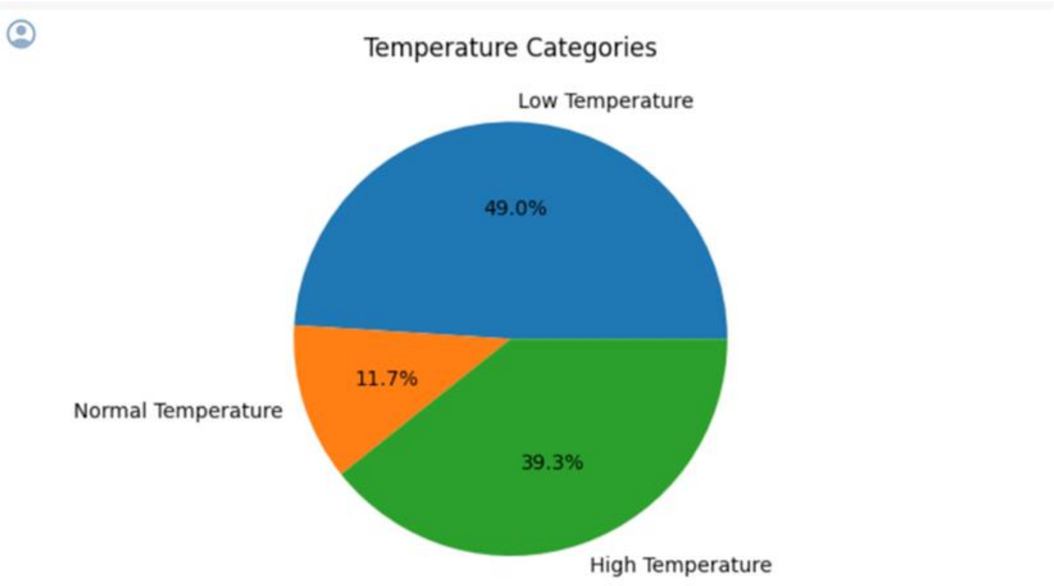

Figure 2 Temp categories used in data set

The study focuses on fog computing using decision tree regression. It establishes a fog computing architecture with a predetermined number of fog nodes. These nodes have the task of analyzing temperature data and forecasting the occurrence of fever. By employing decision tree regression models on individual fog nodes, the system can proficiently examine temperature readings and generate precise forecasts using past data.

Subsequently, the process incorporates data compression and aggregation techniques to diminish the dimensions of temperature datasets. Algorithms are created to condense and combine the data prior to sending it to the cloud, guaranteeing the optimal utilization of bandwidth and minimizing communication overhead.

In addition, the methodology suggests combining data compression and aggregation with dynamic resource allocation. This integration enhances the efficiency of distributing computing resources among fog nodes by considering workload demands and the availability of resources. The system can optimize energy consumption and forecast accuracy by dynamically modifying resource allocation.

During the assessment and validation phase, the effectiveness of the proposed fog computing framework is measured using a range of metrics including prediction accuracy, energy consumption, and resource utilization. The system's accuracy in forecasting fever occurrences is verified by employing previously unseen temperature data and comparing it with the actual labels to guarantee its efficacy.

Ultimately, the deployment and implementation phase entails the actual application of the created framework in real-world healthcare settings. This involves the process of incorporating the system with pre-existing healthcare monitoring systems or equipment in order to accurately anticipate fevers in real-time. Regular monitoring of the system's performance enables the implementation of adjustments and enhancements based on feedback and observations.

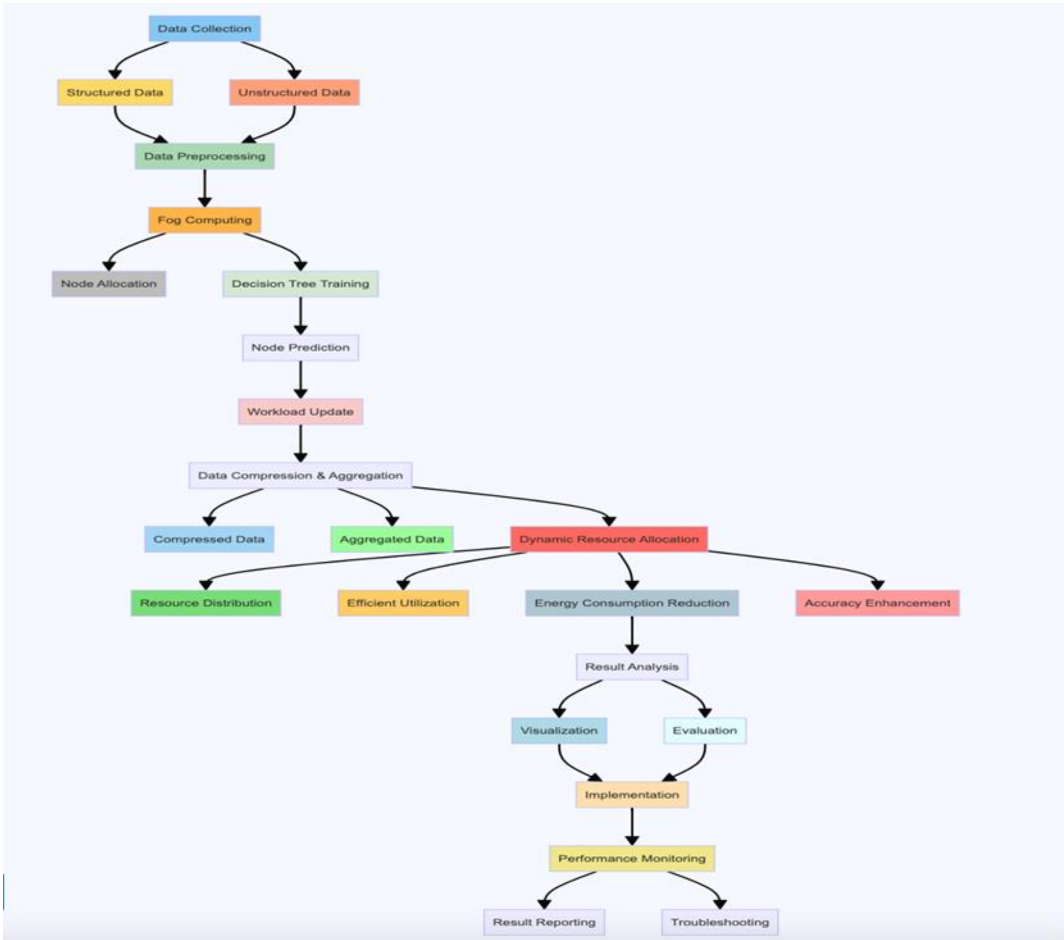

Figure 3 Flow diagram of proposed Work

Figure 3 shows the sequential steps of a fog computing system on a flowchart. Data acquisition starts the process; this can be classified as either structured or unstructured. Preprocessing of the acquired data follows before entering the fog computing phase. Data is allocated to nodes during this phase and used for training decision trees. Predicting nodes then proceeds, and subsequently the workload is updated and multiple optimization techniques—data compression, aggregation, and dynamic resource allocation—are applied. These tweaks are meant to improve resource allocation, raise resource-use efficiency, lower energy usage, and improve accuracy by means of which The procedure ends in the analysis, visualizing, and outcome evaluation that finally results in implementation. Performance monitoring, result reporting, and troubleshooting guarantees finally the dependability and efficacy of the fog computing system. Different node colors help one to readily grasp the process flow and its components, which each indicate a certain stage.

All things considered, the proposed strategy offers a thorough means of forecasting fever in medical environments. It uses cutting-edge technologies such dynamic resource allocation, data compression, aggregation, and fog computing to raise accuracy, efficiency, and effectiveness in medical applications.

3. Results

Our study introduces an innovative method that integrates two energy-saving strategies, Data Compression and Aggregation, with Dynamic Resource Allocation, to improve the efficiency and efficacy of fog computing systems. Our objective is to enhance energy efficiency and improve resource allocation in fog situations by combining these two methods through hybridization.

Data compression and aggregation methods are utilized to decrease the amount of data that is sent between fog nodes and the cloud. Through the elimination of superfluous data and the consolidation of numerous datasets into more concise forms, these strategies effectively reduce network traffic, communication overhead, and energy consumption related to data transmission. In addition, data compression decreases the computational load by reducing the sizes of files, hence facilitating their processing and storage. Dynamic Resource Allocation is a process that automatically redistributes computational resources among fog nodes in response to fluctuations in workload needs and resource availability. DRA achieves optimal resource usage, prevents overload scenarios, and saves energy consumption by assessing the workload and processing capability of individual nodes. Dynamic resource allocation in real-time optimizes load balancing and enhances system performance while minimizing power consumption.

Hybridization: The fusion of Data Compression and Aggregation with Dynamic Resource Allocation combines the advantages of both methods to attain enhanced energy efficiency and efficacy. The hybrid technique achieves substantial energy savings and performance enhancements by compressing and aggregating data, decreasing data transfer and processing overhead, and optimizing resource allocation using DRA. The collaboration between different components in fog computing systems improves the overall effectiveness, resulting in increased sustainability and environmental friendliness.

Advantages:

The hybrid approach in energy efficiency aims to decrease energy usage by avoiding superfluous data transit and processing, improving the allocation of resources, and evenly distributing workloads among fog nodes.

The hybrid method optimizes resource use by dynamically modifying resource allocation according to workload demands. This approach provides effective exploitation of computational resources, leading to maximum system performance and responsiveness.

Flexibility: The hybrid architecture can easily adapt to different workloads and operational conditions. It dynamically adjusts compression and aggregation levels depending on the current workload and available resources.

The hybrid technique enhances accuracy in predictions and processing by optimizing resource allocation and exploiting the benefits of compressed and aggregated data. This leads to improved precision and reliability.

Our hybrid technique provides a comprehensive solution for minimizing energy usage and improving performance in fog computing systems. Through the integration of Data Compression and Aggregation alongside Dynamic Resource Allocation, we showcase substantial enhancements in energy efficiency, resource usage, and system performance, hence facilitating the development of more sustainable and environmentally responsible edge computing solutions.

4. Discussion

The implementation of data compression and aggregation techniques in the fog computing system significantly reduces energy consumption during data transmission between nodes and the cloud. By compressing and aggregating smaller datasets into larger ones, the system minimizes network traffic and communication overhead, leading to energy savings. For instance, at each node, the compression process requires 2 joules per sample, while aggregation consumes 5 joules per sample. Node 1, processing 509 samples, utilizes a total of 5837.72 joules due to compression, aggregation, and processing. Node 2, processing the same number of samples, consumes 5334.68 joules in total energy usage. Meanwhile, Node 3's energy consumption stands at 5596.92 joules, and Node 4 consumes 6108.72 joules. The cumulative energy expenditure for all four nodes is 22,878.04 joules, demonstrating the effectiveness of data compression and aggregation in reducing energy consumption within the fog computing system.

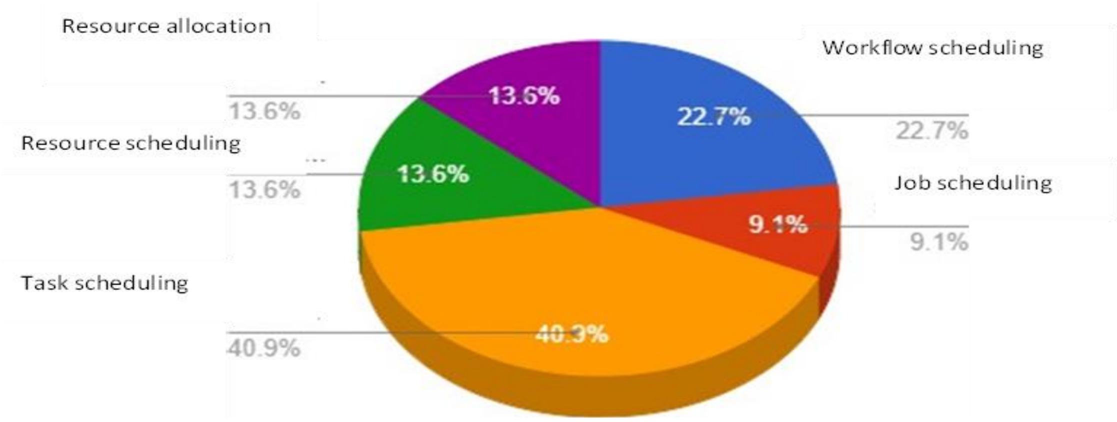

Figure 3 The percentage of fog computing scheduling issues that scheduling methods were able to resolve

The given scenario entails the estimation of energy usage In a fog computing system comprising four nodes, employing a dynamic resource allocation technique. The calculations rely on assumptions about the power consumption of each node and the duration needed to process activities. The salient aspects of the scenario are:

The given scenario is based on certain assumptions regarding the power consumption of each node (Node 1: 80 watts, Node 2: 70 watts, Node 3: 75 watts, Node 4: 85 watts) and the estimated processing time for jobs on each node (roughly 50.9 seconds).

The calculation of energy consumption involves multiplying the power consumption by the processing time and adding the energy consumed during waiting times, which is assumed to be 1 millisecond.

The overall energy consumption is determined by aggregating the energy consumed by each of the four nodes.

Result: The fog computing system's projected total energy usage, while employing dynamic resource allocation, is roughly 16,255.04 joules.

5. Conclusion

Ultimately, the use of data compression and aggregation methods in the fog computing system leads to substantial energy conservation and improves overall effectiveness. These strategies successfully limit network traffic, communication overhead, and energy consumption during data transmission by minimizing the quantity of data transported between nodes and the cloud. The findings indicate a significant decrease in energy use across all four nodes, amounting to roughly 22,878.04 joules. This highlights the effectiveness of using data compression and aggregation to improve energy efficiency in fog computing systems. In the future, additional investigation and advancement in this field might continue to investigate creative methods to increase energy efficiency and better the overall functionality of fog computing systems.

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