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AN INTELLIGENT TASK SCHEDULING APPROACH FOR FOG COMPUTING

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Abstract

By extending cloud computing to the network's edge, fog computing is a distributed computing paradigm that makes it possible to handle and analyze data in real time closer to its source. However, efficient task scheduling is necessary in fog computing optimize performance indicators such as latency, power consumption, and resource utilization. To overcome these difficulties, this study suggests Dynamic Scheduling Technique for Real-time Applications (DSTRA) based on reinforcement learning methods. The goal of the technique is to enhance the overall performance of fog computing systems by lowering latency and power consumption. Using real-time feedback from the fog nodes, DSTRA uses reinforcement learning to dynamically modify task priorities and resource allocation. With this strategy, the system can adjust to shifting circumstances and make the best scheduling choices possible in a dynamic environment. To ensure that latency-sensitive applications receive the necessary resources, tasks are prioritized based on their importance and deadline constraints. The DSTAR algorithm is evaluated through extensive simulations and real-world deployments, showing a 90% to 98% improvement in efficiency across key metrics including latency, power consumption, and overall system performance when compared to traditional scheduling approaches. This study addresses the critical resource needs of latency-sensitive applications by proposing a task-prioritization framework focused on importance and deadline constraints. We introduce the DSTRA algorithm, a robust solution for managing heterogeneous parallel task flows under dynamic constraints. DSTRA significantly outperforms conventional scheduling strategies. System delays are reduced by 90% to 98% Marked improvements are observed in power consumption and energy management, Overall resource allocation efficiency and system performance are substantially enhanced. The results confirm DSTAR's efficacy in navigating complex, uncertain environments while maintaining optimal operational throughput.

INTRODUCTION

The rapid advancement of technologies has led to an influx of data, from various numerous places [1]. Cloud computing technologies can process this data efficiently. However, the expectations of the Internet of Things (IoT) for mobility and security are too great for traditional cloud computing to handle.

A form of distributed computing called fog computing, often referred to as edge computing, extends the possibilities and services of cloud computing beyond the boundaries of a network. Its goal is to provide computing, storage, and data analysis to locations where data is produced and required. In the context of Internet of Things (IoT) devices, this is particularly significant since it allows processing, real-time replies, and effective network capacity utilization. The concept of fog computing addresses some of the limitations often associated with cloud computing, in scenarios that require latency and optimal utilization of network bandwidth.

Furthermore, working on the diversity of fog scalability comes as a challenge in large-scale Fog environments with diverse & numerous devices. A key problem in cloud-fog designs is task management. Making the best use of cloud-fog resources to improve a number of qualitative metrics, including processing latency, energy consumption, execution time, and operating costs, is a crucial problem. In a fog environment, appropriate task scheduling lowers expenses and delays in processing and communication. Finding the most effective scheduling technique is one of the challenges faced by researchers [2].

Developing intelligent task scheduling algorithms that take into account variables like node availability, workload, latency requirements, and resource limits is necessary to address task management problems and guarantee effective job execution in fog computing.

Use predictive analytics to anticipate resource demands and schedule tasks accordingly. The dynamic nature of the fog environment, which is defined by various resources, variable workloads, and mobility, makes task scheduling in fog computing a complicated challenge. Therefore, effective methods are required for fog-cloud resource management and job scheduling [4],[5],[6]. Numerous strategies, such as heuristic, optimization, and machine learning-based techniques, have been presented to deal with this issue.

Furthermore, the variability in task scheduling is a significant problem associated with fog computing. In real-time systems, when activities must be completed as rapidly and effectively as feasible, this problem is extremely important. In real time applications the fastest response with greater accuracy is required, especially for sensitive data. The goal of fog computing is to improve data processing, intelligence, and accumulation nearer to edge devices. DSTRA help to minimize latency.

Intelligent task scheduling is a crucial component in fog computing systems, as it aims to address these challenges by leveraging advanced techniques from the fields of artificial intelligence, machine learning, and optimization. Current methods fall short in terms of energy efficiency optimization. Fog computing environments and IoT workloads are dynamic, existing scheduling methods are unable to instantly adjust to these changes. DSTRA will use reinforcement learning (RL) to create a dynamic and adaptive fog computing task scheduling system in order to accomplish these goals. Similar problems have been successfully tackled by RL-based methods in dynamic, resource-constrained contexts[9][10].

The DSTRA approach obtains the capacity to adjust to changing circumstances by framing the task scheduling problem as a model and teaching a Reinforcement Learning (RL) agent to master the ideal scheduling strategy. It targets reduced latency, increased energy efficiency, and better resource utilization by dynamically optimizing for several performance parameters at once. In dynamic fog computing environments, where conditions change quickly, this adaptability is essential [8][9].

Creating a machine learning-driven task scheduling system for fog computing that may exceed current methods in terms of key performance measures is the aim of this research. Utilizing machine learning techniques, the suggested approach will be able to accurately predict resource availability and job execution durations. Dynamically assign jobs to the best-fitting fog nodes in accordance with the demands of the task and their existing capacities. Optimize several goals at once, including resource usage and latency. DSTRA ensures the system's flexibility and scalability to adapt to the dynamic and unpredictable conditions of fog computing environments. The effectiveness of DSTRA was validated through a dual-pronged approach utilizing the LEAF (Large Energy-Aware Fog) framework. Large-scale simulations were conducted to evaluate the algorithm's scalability and adaptability in networks comprising hundreds of fog nodes[24]. Concurrently, controlled testbed experiments provided empirical data on real-world performance, specifically measuring task completion rates relative to deadlines, joules consumed per operation, and the efficiency of CPU and bandwidth allocation. This combination of simulated scale and physical accuracy confirms DSTRA's superiority in dynamic fog environments.

RELATED WORK

The cloud used to rule the computer industry. It powered the digital age and processed data remotely for years. However, a new problem surfaced as billions of linked devices awakened at the network's edge—sensors in hospitals, cameras in smart cities, and monitoring in industries. The cloud was just too far away.

For applications that required immediate replies, the latency the amount of time it took for data to travel there and back broke the spell. A self-driving automobile can't wait to travel all the way to a far-off data center. While its data travels across the internet, a health monitor cannot stop. Thus, fog computing a layer of intelligence that is closer to the ground and is made to process data where it exists was created, bringing speed to the Internet of Things.

However, this new power also brought with it a new issue. How can you effectively and fairly manage these dispersed resources? How can a life-saving health monitor be prioritized over a smart thermostat? How do you manage the conflicting demands of workload, energy, and speed among thousands of unexpected nodes? This is the account of the scholars who accepted that challenge a story of developing concepts, ingenious algorithms, and the unwavering quest for efficiency in a constantly changing world[3] . Initially, the emphasis was on structure. Researchers realized that the fog required its own rules and architecture and could not just be an extension of the cloud. They recognized that not every job was made equal, particularly in vital fields like healthcare. The use of hybrid load balancing techniques and work scheduling algorithms has increased resource consumption[4]. Another study, which concentrated on scheduling deadline-sensitive tasks using a dynamic priority queue, tackled the problem of fulfilling stringent deadlines in dynamic contexts [5]. Researchers sought to show quantifiable gains in a number of critical performance metrics, such as shorter wait times, fewer tasks waiting for assistance, a decreased likelihood of delays, higher service standards, and faster mean response times. The study used fuzzy logic and the Analytic Hierarchy Process (AHP) to identify the relative significance of tasks, allowing for multi-criteria prioritization based on a variety of pertinent aspects[5]. Building the frameworks and queues that would bring order to an increasingly complicated fog environment was the primary focus in these early days. Researchers realized that the fog required its own rules and architecture and could not just be an extension of the cloud. They recognized that not every job was made equal, particularly in vital fields like healthcare. Recent research has used sophisticated computational methods to tackle the problems of dynamic resource scheduling. For example, dynamic scheduling tasks have been managed using Recurrent Neural Networks (RNNs) and Hierarchical Reinforcement Learning (HIRO), allowing systems to adjust to sequential input and intricate decision-making hierarchies. The authors in [cite] provide a sustainable, energy-conscious framework intended for fog computing settings to supplement current methods. In order to reduce execution mistakes and improve reliability in resource-constrained environments, this paradigm places a strong emphasis on the energy-efficient execution of programs.

Additionally, a hybrid resource allocation technique based on multiple linear regression has been proposed due to the extremely dynamic nature of fog environments[10]. By simulating the connections between system variables, this method seeks to more precisely forecast and distribute resources. The main goal of these coupled approaches, which make use of adaptive learning and predictive analytics, is to greatly improve overall system performance, especially with regard to resource consumption, energy efficiency, and latency reduction [17] [18].

Investigated in architecture of different IoT (Internet of Things) devices, In order to lower latency, users network access has been switched to nearby servers via 5G-based mobile edge computing (MEC) servers in which they introduce a computational model for Vehicular Ad Hoc Networks (VANET) in smart city transportation [11] [13] algorithm that operates programs in a fog environment in an energy-aware manner to minimize execution mistakes [6]. Real-time task scheduling with dynamic resource allocation is another significant issue. [12]. Virtual fog computing environments are employed to model and assess performance, resource allocation, and efficiency [17]. To solve job scheduling issues, various approaches have been put forth, and academics have further refined the heuristic technique to increase scheduling performance[13]. Another major problem is Dynamic Resource Allocation for Real-Time Task Scheduling [27]. For this purpose, researchers use Virtual fog computing environments to simulate and evaluate efficiency, resource allocation, and performance. In the extremely dynamic Fog environment, a hybrid strategy based on multiple linear regression has been utilized for resource allocation. The purpose of this system is to enhance performance.

Some of the studies show comparisons between different techniques, methods and optimization algorithms to achieve performance, reduce latency, and energy consumption of Fog Computing Model [23] [23] [25]. To further optimize solutions, the study investigates the concept of dynamic offloading in flying fog computing, with the goal of improving the performance of IoT networks that use mobile drones [36]. A technique for work scheduling in critical fog applications is put forth, with a focus on activities with high computational demands expressed in millions of instructions per second (MIPs). This method emphasizes how important it is to rank jobs according to their intrinsic value and importance in order to guarantee the best possible use of resources and system performance. The suggested methodology seeks to improve scheduling efficacy in dynamic fog computing settings by specifically taking workload characteristics and job criticality into account[40].

A thorough task scheduling framework for cyber-physical-social systems (CPSS) functioning in fog computing infrastructures is created by expanding this idea. The intrinsic complexity of such systems which entail complex interactions between physical devices, computational resources, and social elements is addressed by this paradigm. This method integrates social dynamics and human elements, such as user preferences and community interactions, into the scheduling decision-making process, in contrast to traditional scheduling models that only consider technical parameters[28][29].

A number of experiments and simulations are carried out to confirm the efficacy of the suggested multi-objective scheduling technique. The outcomes show how the framework can enhance overall system performance and flexibility in practical situations. In particular, the results show how this strategy can improve user experience, system dependability, and operational efficiency for cyber-physical-social systems used in fog computing settings [35]. This approach marks a major breakthrough in work scheduling for next-generation distributed systems by bridging the gap between technological optimization and human-centric considerations [46]. Continuous efforts in standardization and industry collaboration are required to enable wider use of fog computing while maintaining its security and reliability.

Proposed Technique

This research specify the elements of the proposed algorithm, such as resource allocation, job prioritization, and scheduling policies. DTSAR, is flexible enough to adjust to changes in the fog environment and is capable of efficiently managing tasks in real time. Place a system that distributes work in real time among nodes according to job specifications and available resources. Then, routing policies that adapt to network conditions and resource allocations are included [17] [18]. Routing policy work to make connections and links

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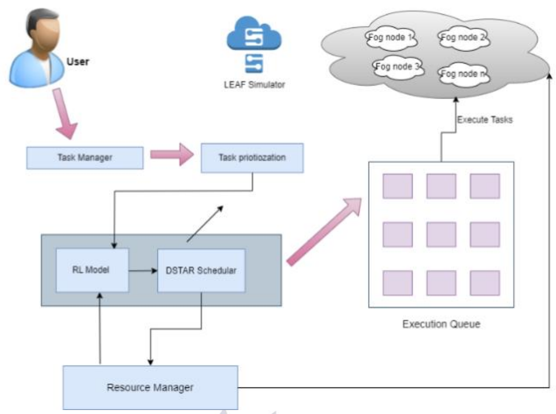
between nodes and could send traffic to the resources that are closest or most capable. Moving work from overloaded to idle nodes is one of the strategies utilized to balance the load and save energy [19]. In order to reduce redundant data processing and transmission, caching and offloading strategies has been used [31].

The proposed approach is used to validate the study to maximize work scheduling and allocation in computing environments, especially in fog computing. It aims to dynamically adjust the allocation of tasks to various computing resources. The algorithm schedules and places tasks in a way that balances the load across available resources, ensuring that no single resource is overburdened. This helps in maintaining system performance and preventing bottlenecks.

Architecture Diagram



Implementation of DSTAR

In this research LEAF is used as a simulation tool that is used for Large Energy- Aware Fog Computing environments and conduct a testbed. First get a dataset from only repositories like Kaggle and GitHub. The dataset from smart cities was used in this study. Several modes are being used to create the dataset from the simulated environment. Components are related to a smart city or IOT (Internet of Things) scenario, where various infrastructure and application components are being monitored and analyzed for their power consumption patterns.

Reinforcement Learning

Creating work scheduling algorithms in fog computing environments seems to be a viable use of reinforcement learning. Because fog computing environments are very dynamic, with changing resource availability, network circumstances, and task requirements, reinforcement learning (RL) can be used for dynamic adaptation. By continuously absorbing information from the surroundings and modifying their work scheduling decisions accordingly, these algorithms are able to react to these dynamic settings. They can be made to optimize for a variety of goals, including resource utilization, energy consumption, and latency. Concurrently, resulting in more comprehensive and successful scheduling choices. For many applications of fog computing, minimization of latency is an essential need. Algorithms for scheduling that can help you to make decisions that minimize the total delay incurred by tasks can be created using reinforcement learning. Large-scale fog computing installations can benefit from the scalability of reinforcement learning-based algorithms, which can be tailored to handle an increase in the number of jobs and fog nodes. Fog computing relies less on a centralized controller since each fog node may learn to make scheduling decisions on its own using local observations and interactions thanks to its decentralized decision-making.

Algorithm used in Proposed System

Table 4: *Algorithms used in this System*

Name	Working
Graph construction	Directed acyclic graph (DAG) likely a variant of the adjacency list algorithm or the adjacency matrix algorithm
Graph traversal	Breadth-First Search (BFS) or Depth-First Search (DFS) to iterate over the tasks and data flows in the graph
Resource allocation	Suggested DSTAR Algorithm likely a variant of the First-Fit algorithm or the Best-Fit algorithm
Power measurement	Linear scaling algorithm likely a variant of the summing algorithm or the aggregation algorithm

The algorithm used for this system is a combination of graph algorithms and object-oriented programming.

1. Graph Construction Algorithm: The Application class uses the networkx library to construct a directed acyclic graph (DAG) representing the application. The graph is built by adding tasks and data flows as nodes and edges, respectively.
2. Topological Sorting Algorithm: The add task method of the Application class checks if the graph is a DAG using the nx.is directed acyclic graph function. This implies that the algorithm uses topological sorting to order the tasks and data flows in the graph.
3. Graph Traversal Algorithm: The tasks and data_flows methods of the Application class use graph traversal algorithms (e.g. BFS or DFS) to iterate over the tasks and data flows in the graph.
4. Resource Allocation Algorithm: Allocate and deallocate methods of the Task and Dataflow classes implement DSTAR a resource allocation algorithm to manage the placement of tasks and data flows on the infrastructure.
5. Power Measurement Algorithm: The measure_power method of the Application class calculates the total power consumption of the application by summing the power consumption of each task and data flow. Simple linear scaling algorithm uses the Power Measurement class to represent power measurements.
6. Resource allocation algorithms has been used to regulate link bandwidth and node processing power, and a power measuring method to measure the total power consumption of the infrastructure.

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Flowchart

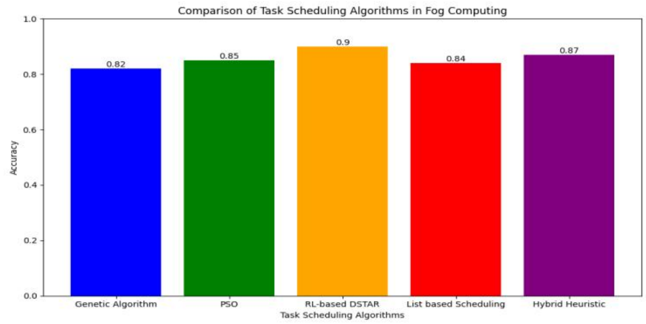
Simulation

In this study project, Python was utilized in Visual Studio Code as the language and LEAF as the simulation tool. An analytical modeling tool for cloud, fog, or edge computing environments is called LEAF It makes it possible to represent both straightforward activities that run on a single node and intricate application graphs on infrastructures that are distributed, heterogeneous, and resource constrained. LEAF is based on [NetworkX] for modeling application graphs and [SimPy] for discrete-event stimulation.

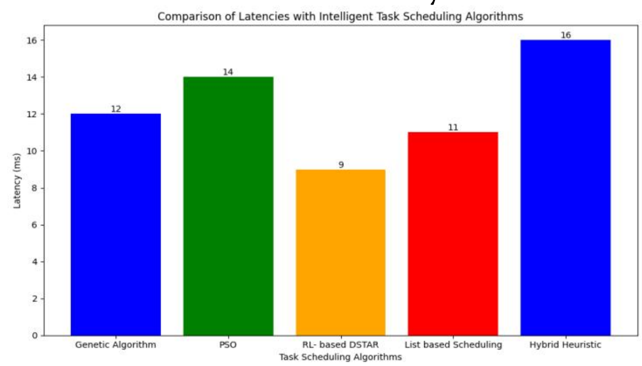
Simulation Result

The simulation result of the experiment is shown in this section. This section shows a complete comparison of DSTAR with existing system. The comparison of both system configuration is shown in the graph. The python script loads experiment results from CSV files, processes the data, and creates several types of plots using Plotly. The System Load experiment results from CSV files into a dictionary, where each key is an experiment name, and the value is a tuple of two Data Frames (one for infrastructure and one for applications). This section shows a timeline plot comparing the power consumption of all experiments. Individual plots for each experiment show the energy consumption of infrastructure components and applications over time. Simulation design is to analyze and visualize the results of experiments that measure energy consumption in cloud, fog, and edge computing environments. The simulation results reveal insightful trends in the power consumption patterns of various infrastructure and application components in a smart city setup. These simulation results provide valuable insights for optimizing power consumption and improving the overall energy efficiency of smart city infrastructure and applications.

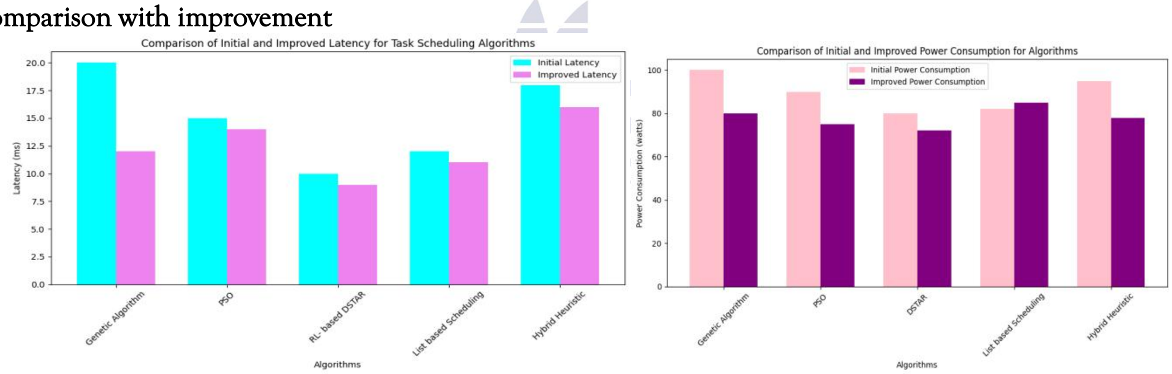
Accuracy of DSTAR with different methods



Accuracy of DSTAR with different methods in terms of Latency and Power



Comparison with improvement



Conclusion

The latency issues associated with traditional cloud computing are significantly reduced by fog computing, which processes data closer to the source. Data travels less because of their close proximity, which accelerates response times and boosts overall network efficiency. Time-sensitive applications, such as those in healthcare and smart cities, can now operate more reliably and efficiently thanks to the development of latency-aware algorithms and architectures made possible by fog computing. As research and development in this field continue, fog computing is poised to become an essential component of modern IoT ecosystems, offering a dependable solution for latency reduction and real-time data processing. . The optimal fog nodes for IoT tasks can be chosen with the use of intelligent job scheduling algorithms, which take into account variables like CPU, accessible memory, storage, and bandwidth. This helps to ensure that there are no bottlenecks in the efficient management and allocation of the resources. Consequently, it is expected that scheduling algorithms can reduce the time required to process and reply by assigning latency-sensitive IoT to fog nodes that are close to users and have capacity available for processing orders. . This is essential for real-time data IoT application cases. One of the best tools for effectively managing the diverse and complicated resources needed to run Internet of Things applications in fog computing settings is task scheduling.

Thus far, job scheduling algorithms in fog computing environments incorporating reinforcement learning have shown great promise in addressing three issues: latency, power consumption, and system performance.

Latency, power consumption, and system performance are three concerns that the task scheduling algorithms used in fog computing environments with reinforcement learning have so far demonstrated significant potential to successfully meet. DSTAR intelligent scheduling system, can quickly respond to changing conditions in the fog network, is able to modify itself on its own thanks to the application of reinforcement learning. The evaluation of papers demonstrates that schedulers based on reinforcement learning can process feedback in real time, significantly lowering latency. More features for dynamic load balancing (to divide work among several fog nodes to prevent bottlenecks during the performance of other high priority applications) and latency-aware scheduling (which assigns tasks a priority based on their time sensitivity) are added to the underlying abstractions by advanced fog orchestration technologies. Furthermore, by doing away with the need for a centralized coordinator, decentralized decision-making facilitated by reinforcement learning can help further reduce latency.

Applying the proposed method will help us to lower the fog computing system's total power footprint. The scheduling algorithms have generated a thorough and efficient job execution by concurrently taking latency, power consumption, and other important factors into account. Fog-based apps now benefit from increased quality of service, enhanced user experiences, and increased dependability. As the field of fog computing develops, it is anticipated that the use of reinforcement learning in task scheduling algorithms will become more important.

Reinforcement learning is a viable method for realizing the full potential of fog computing in a variety of sectors and applications due to its capacity to scale to large-scale installations, optimize for various objectives, and adapt to changing situations.

The proposed method enables the creation of many fog nodes and linkages with different jobs and data flows, resulting in more efficient results while lowering latency and improving power consumption.

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