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Novel Resource Allocation Approach for Fog Computing-Driven IoT Systems

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Abstract: Fog computing (FC) has the potential to lower latency and boost speed. Internet of Things (IoT) networks have difficulties allocating resources efficiently. The approaches used are flexible, scalable, or optimized. To maximize performance indicators, new approaches that utilize real-time information, workload sequences, device accessibility and network circumstances are required. We investigate the allocation of resources and task scheduling for numerous devices in IoT systems in this research. IoT devices must properly choose which data to offload to FC nodes (FCNs) as they acquire enormous amounts of data. To tackle the problem of supporting multiple device connections and facilitating fast data transfers with constrained resources, we suggest executing non-orthogonal multiple access (NOMA). Several devices can simultaneously send data spanning time, frequency and coding domains to an identical FCN because of NOMA. Together, we optimize power transmission and resource assignment for IoT devices, meeting QoS requirements and reducing network energy usage. In this research, a unique boosted atom search optimization (BASO) method is presented to tackle it because it is an NP-hard issue. According to the simulation results, the suggested strategy outperforms in terms of greatest throughput, minimum latency and optimal energy use.

Keywords: *Fog computing (FC), Internet of Things (IoT), resource allocation, energy usage, boosted atom search optimization (BASO)*

1. Introduction

Fog computing (FC) is complicated and dynamic, making resource allocation (RA) difficult in smart environments and particularly in the IoT. As user demands evolve, resource allocation and management must become more dependable. Systems for managing and allocating resources effectively must be built to adapt the changing demands of its users [1]. Not all fog-specific software is executed by fog devices. The lack of wireless connectivity, device autonomy and centralized management in the fog environment might result in resource and connection problems.

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In response to the increased need for processing, network and storage capacity to be expanded nearby to end users, FC has emerged as a possible alternative that can complement cloud computing fragility [2]. Since this is a new paradigm, there are a number of outstanding research problems and obstacles to be solved. One of these difficulties is allocating computational resources, which attempts to give the service or application the resources it needs to meet the specified performance and Quality of Service (QoS) metrics acceptably [3]. Using the processing power of fog devices, the FC environment is a state-of-the-art processing architecture that enables application services to be delivered to clients faster and more effectively. Certain convergent-structured devices can function as fog nodes (FNs), providing users with networking, computation and storage capabilities [4]. The shape, structure and functionality of convergent structured devices are different from those of classical computational devices. The dominant use of dynamic contexts, similar to the IoT, in a FC environment, can result in unpredictable events, like high response times, decreased reliability and unavailability of services, when combined with intense competition for limited computational resources [5]. Utilizing RA techniques from other computational paradigms, such as cloud computing, is not without its challenges. It is critical to comprehend the suggestions that have been made and the obstacles that need to be conquered [6]. In FC, different edge nodes can cooperate to share interactions, hiding and processing assets to do certain computational assignments locally without requiring links to communicate with the cloud computing center. These FNs can be base stations (BSs), routers, relays and Wi-Fi access points (APs), among other devices [7]. In this study, we investigate the RA approach for fog computing in IoT systems.

The rest of the paper organization is as follows: literature review, methodology, result as well as discussion and conclusion of the paper.

2. Literature review

The research [8] focused on the issue of RA and dynamic offloading in multi-tiered FC systems with traffic prediction. The goal was to minimize the time-average power consumption with a stability guarantee for every queue in the system by rephrasing the problem as a stochastic network optimization problem. Using special issue structures, they provide a distributed as well as effective predictive offloading and resource allocation (PORA) technique for multi-tiered FC systems called predictive offloading and RA, or PORA. The study [9] examined the candidate FNs technique for the FC networks' RA dilemma for energy-efficient (EE) applications. The study [10] presented an agreement index and robustness-maximizing fuzzy logical offloading approach for IoT presentations with unknown parameters. The method of fuzzy offloading was meant to be learned and optimized from a variety of applications using an Estimation Distribution Algorithm (EDA) for estimation. Applications were divided into separate clusters by the algorithm, allowing each cluster to be sent to the appropriate tier for additional processing. Thus, scheduling decisions in a smaller search space saves system resources. The study [11] suggested two approaches, extended classifier system (XCS) and Best classifier memory-extended classifier system (BCM-XCS) to balance the use of energy at the network edge and minimize processing delays in the workload. These methods were founded on learning classifier systems (LCS) and XCS. The outcomes demonstrate that BCM-XCS was better than the standard XCS-based approach. The paper [12] proposed the relationships between Authorised Data Service Subscribers (ADSSs) and Data Service Operators (DSOs) were modelled as an Equilibrium Problem with Equilibrium Constraints (EPEC) and large-scale optimization solutions were obtained through the use of the Alternating Direction Method of Multipliers (ADMM). The DSOs' optimized resource price and the ADSSs' estimated resource purchases. The paper [13] presented the challenge of using parked cars to distribute the scarce fog resources among vehicular apps in a way that minimized service delay. Next, they suggest utilizing a heuristic method to effectively identify the solutions for the issue formulation. The article [14] presented a QoS-aware RA scheme that consider the relationship between computational resources, transmission, FNs and ID allocations to enhance the choice of reducing network overhead while offloading. The system aimed to ensure multiple QoS specifications for different types of identification while minimizing the FC network's overhead, involving task procedure latency and consumption of electricity. The paper [15] examined the workloads predicted by the deep auto encoder (DAE) model throughout the analysis step as guidance and fog nodes were scrambled following the requirements of workloads for industrial IoT. The Crow Search Algorithm (CSA) was developed to increaseprice and latency goals were linked using the structure for optimum FN choice. The suggested plan was assessed and contrasted with the current optimization models concerning response time, throughput, request rejection ratio and execution cost. The study [16] addressed an RA method utilizing collaborative machine learning (CML) for Software defined Networking (SDN)-enabled FC. The RA method for the SDN-enabled fog-based computing environments was linked with the suggested CML model. Several performance evaluation criteria, including bandwidth utilization, energy consumption, latency, waiting and time to execution, were used to test the outcomes of the proposed methodology utilizing the FogBus and iFogSim. The work [17] introduced a novel approach for fog environments, called Methodology for Effective Prediction and Resource Allocation (EPRAM) that can be used in healthcare environments. With a variety of RAs, it was a difficult undertaking because of the resources and fog nodes required to do the computations required for IoT systems.

3. Methodology

This section presents the network model of the situation under consideration, together with the network, computation and communication models for the FC-based IoT use NOMA.

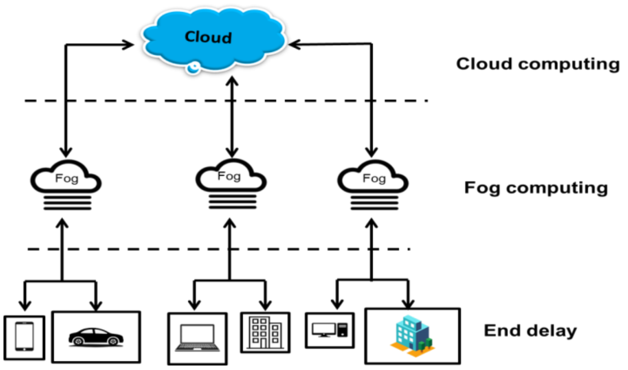

Fig.1 Wireless IoT systems based on fog computing

3.1 System model

3.1.1 Network model

IoT device offloading services are provided by dedicated FNs. In actuality, routers, access points, network edge nodes, or switches are typically the ones that play these FNs. IoT networks contain a vast array of devices, such as smartphones, wearable technology, cameras, sensors and more. They can produce enormous volumes of information and facilitate several applications based on computation, each with specific deployment requirements. For FC-based IoT systems, we choose a broad system approach, as illustrated in Fig. 1.

3.1.2 Communication model

The communication framework for IoT networks using NOMA is presented in this section. A group of IoT devices would use varying power levels to deliver the FN on the same RB with their data in an uplink NOMA system. Assuming that the $m^{th}$by sending a signal, an IoT device transfers compute work to the FN for processing. w_j^lusing transmissions power o_n^l on the l^{th}From the RB to the FN. The signals that were received z_n^l from the m^{th}IoT gadget on the l^{th} RB can be expressed as equation (1).

$$z_n^l = \sqrt{o_n^l g_n^l w_n^l + \sum_{j\neq n, j\epsilon N} \sqrt{o_j^l g_j^l w_j^l + y_n^l}} \quad (1)$$

The intended signal is represented by the first word, in which g_j^lindicates the channel strength for the m^{th}FN on the IoT l^{th} RB devices from IoT on the same RB are represented by the second term. The final term y_n^linvolves assuming a zero mean and variance when calculating additive white Gaussian noise (AWGN). In FC-based IoT systems employing NOMA, several IoT devices communicate their loading information same FN on identical RB. IoT gadgets on the l^{th}RB connected to the same FB are grouped according to the channel gains in decreasing order, which can be shown as equation (2):

$$\left|o_1^l\right|^2 \geq \left|o_1^l\right|^2 \geq \cdots \geq \left|o_1^l\right|^2 \ \forall l\epsilon L \quad (2)$$

These RB orderings suggest that the FN can correctly interpret the superposed signals. As a result, the FN that was acquired the m^{th}device IoT on thel^{th}RB is provided by equation (3).

$$SINR_n^l(o) = \frac{o_n^l\left|o_n^l\right|^2}{\delta^2 + \sum_{j=n+1}^{N} o_j^l\left|o_j^l\right|^2} \quad (3)$$

The matching information rate of the m^{th}IoT gadget that communicates with the FN on the l^{th} RB is represented by equation (4).

$$Q_n^l(o) = log_2(1 + SINR_n^l) \quad (4)$$

Following this, the possible level of the data m^{th} IoT device is shown in equation (5).

$$Q_n = \sum_{l\epsilon L} a_n^l \mathcal{R}_n^l \quad (5)$$

Where a_n^lrepresents the outcome of the allocation of IoT device RBs, with $a_n^l = 1$ representative of the l^{th} the RB is designated to m^{th}an offloading IoT device else $a_n^l = 0$.

3.1.3 Computational model

We consider that the computational the IoT device's attempt is separated into many jobs. These professions can be finished remotely or locally on the device by connecting wirelessly to the FN. Memory, networks and central processing units (CPUs) interface capabilities can be represented as multi-dimensional vectors in the generic computing resource model of the FN. We assess the computational cost for the FN and local computing modes respectively, regarding processing duration and energy consumption.

➢ **Compute locally**

Each IoT device employs its processing capacity to carry out computation assignments on-site when using the local computing technique. Computation execution time is the proportion of the entire amount of cycles on the CPU required for the task allocated to the nearby computer resources of the m^{th} task of the n^{th} local computing is used by an IoT device and it is decided by equation (6):

$$S_{nm}^k = \frac{C_{nm}}{D_{nm}}, \forall n \ \epsilon \ N, m\epsilon M \quad (6)$$

The power needed to n^{th}local task on the device M afterward, processing can be decided upon using the energy usage data. This can be stated as equation (7):

$$\rho_{nm}^k = \xi C_{nm} D_{nm}^2, \forall n \ \epsilon \ N, m\epsilon M \quad (7)$$

Where $\xi$is the constant that displays the energy used up every CPU cycle. It is reliant on switching capacitance and average activity parameters.

➢ **FN Computing**

Using wireless connectivity, the IoT device transfers its workload to the approved FN in the context of the FN computing strategy. Subsequently, the FN, with ample computational and capacity for storing, would handle these assignments regarding the IoT and transmit the calculation outcomes as needed. There would be an additional time and energy cost associated with using wireless networks to transfer the relevant information between the FN and the IoT devices during the process. We concentrate on the uplink offloading communications in this study since it should be noted that IoT device uplink broadcasts to the FNs typically include enormous amounts of data. The FN's computational capacity for carrying out job M, expressed in terms of seconds per CPU cycle, is called D_{0m}. Assuming that the n^{th} IoT device loads its calculation job $E_{nm}$the transmission time of the data to the FN n^{th}IoT device offloading the m^{th} task is determined by dividing the offloaded task sizes by the data rate of transmission, denoted by equation (8):

$$S_{nm,s}^{d} = \frac{B_{nm}}{Q_n}, \forall n \in N, m \in M \quad (8)$$

In the same way, the calculation execution duration of the m^{th}task of the $n^{th}$the FN's IoT gadget is provided by equation (9):

$$S_{nm,f}^{d} = \frac{C_{nm}}{D_{0m}}, \forall n \in N, m \in M \quad (9)$$

Conversely, the energy required to outsource the work M of IoT device N is specified by equation (10):

$$\rho_{nm}^{d} = \sum_{l=1}^{L} S_{nm,s} O_n^l + \eta C_{nm} D_{0m}^2,, \forall n \in N, m \in M \quad (10)$$

Here η is the FN's CPU cycle's energy efficiency coefficient. It is based on switching capacitance and average activity factors. The first and second components, correspondingly, indicate the energy consumption of transmission and computing energy consumption.

3.2 Optimising the problem of heterogeneous RA

We look at the issue of computation and communication resource optimization based on the above-mentioned system model. The optimization objective is set as system energy consumption and the restrictions take into account the QoS needs of the IoT devices. We achieve QoS standards as well as minimize network energy consumption by optimizing power transmission and resource assignment for IoTs. Because it is an NP-hard problem, a novel boosted atom search optimization (BASO) approach is provided in this study to address it.

3.2.1 Resource Allocation Problem

As the research showed, some several problems and restrictions need to be considered to enable computationally demanding applications in IoTs. The issues include where to do the computation work, how to compute the results effectively and the resources needed for the procedure and the system's energy consumption. A novel boosted atom search optimization (BASO) approach is provided in this study to address these problems.

3.2.2 Boosted Atom Search Optimization (BASO)

In this work, we introduced the BASO approach for the lowest latency and best energy consumption. Boosted Atom search optimization (BASO), a new optimization approach motivated by molecular dynamics, is presented. An improved solution denotes a heavier mass and the opposite is true, according to BASO, which uses the location of every atom inside the search space as a measure of its mass. The population of atoms will all either attract or repel one another depending on how far apart they are from one another, which will cause them to go in the direction of the heavier atoms. Because they accelerate more slowly, heavier atoms actively look for more effective solutions nearby. When lighter atoms accelerate more quickly, they examine a wider area of the search space to discover new, promising places. The definition of the generic unconstrained optimization issues is in equation (11) and (12).

$$minimiw\ e(w), w = (w^1, \ldots, w^C) \quad (11)$$

$$Ka \leq w \leq Va, Ka = [ka^1, \ldots, ka^C], Va = [Va^1, \ldots, ka^C] \quad (12)$$

Where w^c $(c = 1, \ldots, C)$ is the c^{th}element in the search area, ka^C and ka^C are the c^{th}elements of the corresponding lower and upper bounds and C is the search space's dimension. Considering that there are N to solve this unconstrained optimization, atoms in the atom population. The appearance of the j^{th}location of the atom is presented in equation (13).

$$w_j = [w_j^1, \ldots, w_j^C], j = 1, \ldots, M \quad (13)$$

Where $w_j^c(c = 1, \ldots, C)$ is the c^{th}component of the position of the j^{th}an atom in a spatial dimension.

Each atom interacts with others in the early stages of BASO through attraction or repulsion and repulsion can prevent atom over concentration and premature algorithm convergence, improving the capacity to explore the whole search space. The attraction progressively grows stronger and the repulsion gradually becomes less as the iterations go by, indicating a decline in exploration and an increase in exploitation. Fig. 2 shows the flowchart of the BASO. Every atom interacts with every other atom in the final iterations by attraction, proving the algorithm's strong exploitation capabilities.

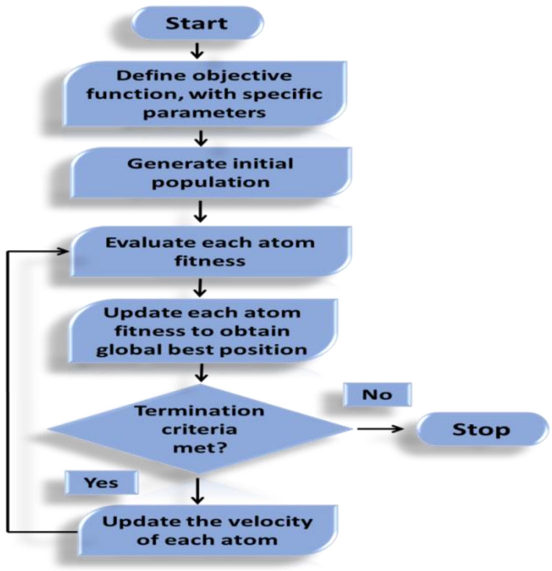

Fig. 2 Flow diagram of the BASO

4. Result and discussion

This section, we evaluate the effectiveness of the suggested optimisation strategy for resource allocation in FC-based IoT networks that use NOMA. Table 1 lists the significant simulation parameters.

Table 1. Parameters for simulation

Simulation parameters	Value
The bandwidth	10MHz
Frequency of carrier centers	2.5GHz
Fading	Rayleigh flat
The radius of the FN	100m
Noise's power spectral density	-174dBm/Hz
Path loss exponent	4
The number of required CPU cycles for task g_{nm}	[0.1-1]GHz
The FN's computational capabilities	20GHz
The data size for task g_{nm}	[0.1-1]Mbits
Computation capacity of the IoT device	[0.7-1] GHz
The energy usage computed by the FN	$1{*}10^{-11}$ J/cycle

Three computational techniques are chosen for comparing the complete computation offloading scheme, which refers to all jobs reloaded at the FN on IoT networks, labelled as everyone offloads and the local computation scheme, which refers to all tasks handled locally at the IoT device. Next, the conventional OMA scheme also known as the "OMA scheme" is used as the benchmark to assess NOMA's performance in cases where many IoT devices are unable to send signals on the same resource block (RB) to the same FN. First, we look at the suggested BASO solution's convergence. The energy consumption of the suggested BASO in comparison to the iterations for various populations is shown in Fig. 3. We have chosen the exhaustive search (ES) scheme as the standard for comparison. It is evident that the suggested approach converges quickly. As the number of iterations increases, the BASO method rapidly becomes closer to the ES scheme.

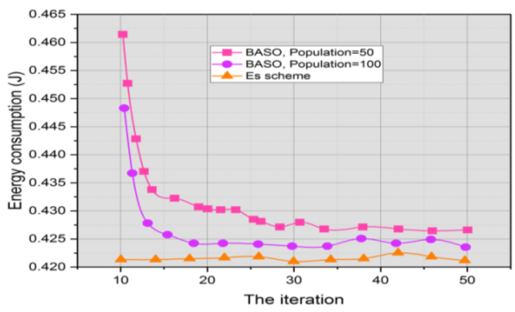

Fig.3 Energy consumption

4. 1 NOMA'S performance

We discuss how the tasks, RBs, number of devices and impact the performance of convergence in Fig. 4. There are 100 people in the population. The graphs shows that additional devices correspond to increased energy usage for convergence when RBs and tasks are the same. In a similar vein, as the number of tasks increases, devices and RBs are equal, so it is the energy required for convergence. Additional RBs translate into additional transmissions offloading of resources, which enhance the performance of convergence even when the devices and workloads remain the same.

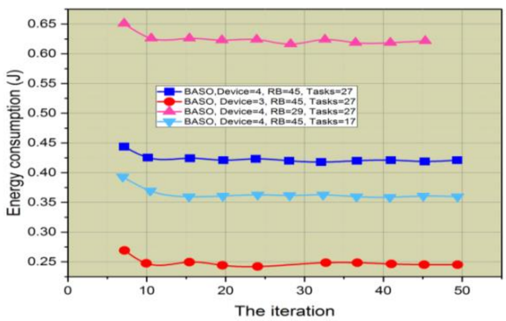

Fig.4 Convergence of performance across tasks, devices, and RBs

We use NOMA to assess the suggested scheme's efficacy. We use a standard OMA scheme as the benchmark for comparison. Fig.5 displays the various maximum transmission powers. The growing trends are caused by the multi-connectivity advantage; by enabling several IoT devices on a single RB, the suggested approach offers a more significant diversity gain. When the maximum transmit power grows, so does the system throughput. Because of the increasing interference between several IoT devices, the system rate in every instance grows more slowly as the transmit power increases.

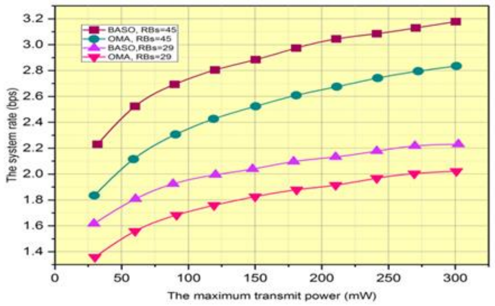

Fig. 5 Transmit power

4.2 Latency performance

We concentrate on the suggested scheme's average latency. Improving resource utilization and satisfying the demands of Internet of Things applications are dependent on the average latency of compute processes. The average delay performance is shown in Fig. 6(a), 6(b) and 6(c) about varying task counts, FN computation capacities and RB counts, accordingly. These numbers show that the suggested design performs better than the schemes that were compared.

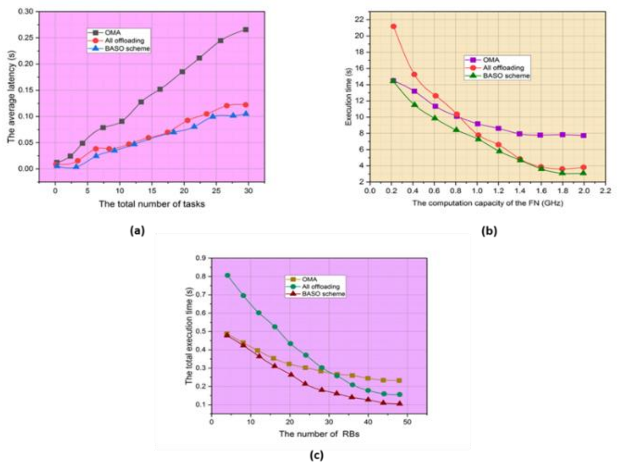

Fig. 6 (a) Average latency vs number of tasks(b) Average latency vs FN's computational capability(c) Average latency vs number of RBs

Fig 6(a), (b), (c) shows that when comparing the suggested plan to the complete loading strategy, the average delay is less. Finally, by transferring information by connecting several IoT devices to the FN and decreasing on time of the transmission, the suggested BASO scheme can achieve superior capacity gain compared to the OMA scheme.

4.3 Energy consumption performance

We concentrate on the suggested scheme's performance in terms of energy usage. The energy usage with varying numbers of tasks, FN calculation capacity and RBs is compared in Fig. 7(a), 7(b) and 7(c), respectively. These numbers show that the suggested scheme performs better than other comparative schemes in FC-based IoT networks with NOMA.

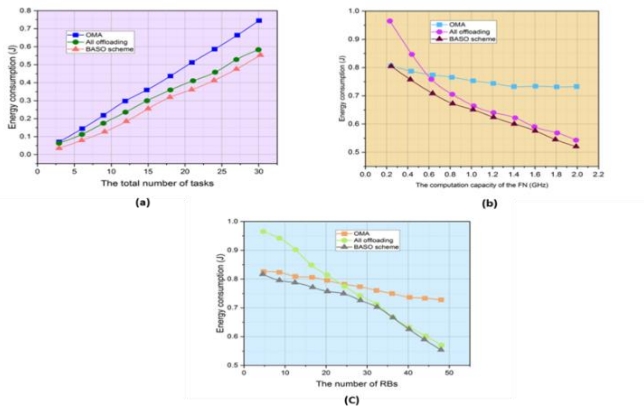

Fig. 7 (a) Energy consumption vs number of tasks (b) Energy consumption vs FN's computational capacity (c) Energy consumption vs number of RBs

Fig. 7 (a) illustrates how the quantity of assignments rises together by the energy usage. When related to another system, the one that completes all tasks locally has the highest energy usage. The FN's far superior computing efficiency of energy than those of IoT devices is the cause. The other three examined schemes the suggested scheme, every offloading and the equivalent system that uses OMA can reduce the consumption of energy use by using the FN's powerful computing and storage resources. Fig.7 (b) and 7(c) shows that comparing the other systems, the proposed BASO scheme reduced the number of RBs and FNs' computational capability.

5. Conclusion

The study has concentrated on the distribution of resources in the IOT systems that utilize FC. We have modeled the price and power usage for FN for both local processing and the delegation of computing activities, considering a general situation with a large number of IoT devices. We achieve QoS standards and minimise network energy consumption by optimising power transmission and resource assignment for IOT. A unique boosted atom search optimisation (BASO) was conducted. We have discovered that the various computing modes can influence the average latency and system energy consumption. A decent performance might be attained by using the suggested strategy, which would make the best selection when selecting the appropriate computing mode. In the future analyse how to use machine learning and edge intelligence to optimize and allocate resources proactively in FC developments. Algorithms for machine learning can evaluate past data, forecast future needs for resources and modify resource allocation plans accordingly.

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