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PERFORMANCE ANALYSIS OF MOBILE-EDGE COMPUTING TASK OFFLOADING STRATEGIES MECHANISMS

Ms.Archana M.S [1] and Dr.N.Anandakrishnan [2]

[1] Research Scholar, P.G and Research Department of Computer Science, Providence College for Women, Connoor, The Nilgiri's District.

[2] Assistant Professor, Department of Computer Science, Providence College for Women, Connoor, The Nilgiri's District.

Abstract: The mobile edge computing is considered to be an arising system for recent data communication in smart or handheld mobile communication terrain. The specified smart mobile bias medium helps to ameliorate their performance effectiveness while using lower energy. According to the particular mentioned energy force, the multitudinous smart mobile bias working aspects may be terminated as a result of the enormous power consumption by different connecting bias abided at mobile communication workstations. The batteries or power source of mobile bias is having a lot of demanding issues. For this reason, this exploration work considering save energy with the help of discharge software modules at colourful occasions take part of mobile data communication through a common communication channel. multitudinous data handling mechanisms in the communication terrain, should concentrate on farther energy over processing data on a mobile device, especially when bandwidth is limited in certain operations will help to transfer a huge volume of data by using minimum energy. Different experimenters proposed and enforced kinds of algorithms are icing "Mobile Edge Computing Task Offloading Strategies" for saving energy. In this exploration paper carry over a performance analysis for Iterated Greedy Taboo Medium Algorithm(IGTMA), calculation offloading in mobile edge computing(COME- UP) and Grey Wolf energy Optimization algorithm(GWO).

Key words: Performance, Energy, offload, Strategy and Mobile Edge.

1. INTRODUCTION

The reduce energy consumption and meet other volume of Services for example Quality of Services related to the job and the calculation unpacking from a mobile device to the remote mobile pall coffers is used to insure that mobile bias profit from energy consumption, recycling capability, the deadline and other former studies linked the locales of the job that bring lower energy consumption on mobile bias. It also gives different scheduling styles to record tasks. Still, being offloading styles didn't consider the dynamic cargo of the system will be a Lacking consideration of system cargo may bring a negative trouble on the scheduling result [4]. Assuming all jobs have lower energy consumption executed on the mobile device, if all those jobs are allocated to the mobile device, this may make the mobile device overfilled, performing in numerous jobs that cannot be finished before deadlines. Though utmost of the time mobile bias have low system cargo, occasional improvement in system cargo occasionally passed in the MCC environment is possible. So, it's essential to consider the dynamic system cargo of mobile bias. With the nonstop development of mobile internet technology, mobile bias are getting lighter and further movable , also with limited computational capacities and battery capacities due to the tackle restriction. The Original mobile bias is in play a main part in the process of whole training. Still, mobile bias isn't born for deep literacy, too important nonstop training will bring a negative impact on their sustainability. In order to define a sequenced offloading decision- making issue for dynamic service migration espoused the Markov decision process. An iterative fashion was suggested to study the task unpacking issue by concertedly examining the allotment of available diapason and computer coffers [5]. In the environment of MEC networks, delved the issues with virtual network embedding and recommended network virtualization. Some related proposed architectures for Mobile Edge Computing performance evaluation is described with a co-operation of data communication layers. Majority of research work exhibits to emplace pall waiters at the edge of the network and allocate the waiters in geographically distributed scales to use the pall to meet the peak loads of requests coming from MEC. The energy optimization algorithms are usually to calculate where it'll reuse the workload (MEC). It use's are general operations that bear a high level of processing to validate their result. It concentrates on the MEC and cloud's capability to reuse large data loads [6].

The main ideal of the paper is to try to reduce the latency between the two layers by assigning weights to the complexities of the tasks to be performed remotely. Some papers concentrate on the problem of energy consumption of mobile bias with the aid of a MEC armature. The optimization problem helps to minimize energy consumption by observing processing time and data transfer. The MEC is working regards to alleviate the battery limitation of IoT bias. The authors have used a facial recognition operation to demonstrate the feasibility of unpacking decision programs. The algorithm includes frequentness of the MEC interface console, CPU cycle, and quiescence rate for energy optimization under the heading of performance evaluation metrics [7] [8].

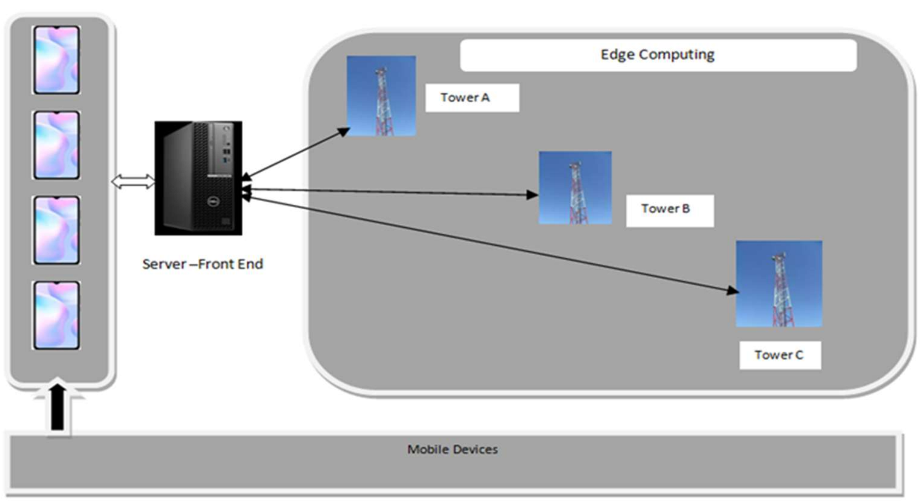

Figure 1.1 Mobile Edge Computing Matrices

The above block diagram (Figure 1.1) depicts a performance evaluation component consideration for mobile edge computing environment, they are: Mobile devices, Server-Font End and Edge computing.

2. RELATED WORK

In this research paper considered three base papers for a performance evaluations are in order to ensure the energy consumption optimization incurred along with MEC: Those papers are Iterated Greedy Taboo Medium Algorithm (IGTMA), calculation offloading in mobile edge computing (COME- UP) and Grey wolf Energy optimization Algorithm (GWO). In IGTMA, the Jobs can be scheduled on mobile devices and cloud resources using a heuristics with iterated greedy taboo mechanism algorithm (IGTMA), according to Junwen Lu et al [1]. The suggested approach offers a good trade-off between energy usage, system load, and project deadlines. The offloading technique ignored the consumers' mobility.

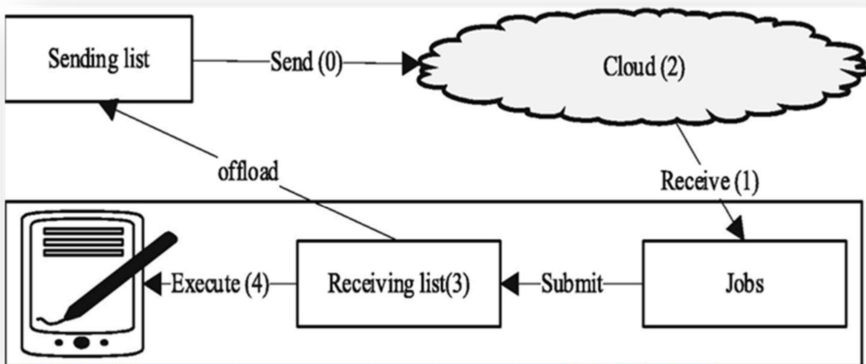

Figure 1.2 MEC job model (https://ars.els-cdn.com/content/image/1-s2.0-S131915782200115X-gr2_lrg.jpg)

The listed jobs are executed on a mobile device or remote cloud resources. Regardless of where the job is executed, it must meet the deadline. The finish time of related execution factors are shown by the below Table 1.1.

Jobs	Job Size (KB)	Execution time(mSec)	Power Consumption(watt)
J1	12.03	0.27	0.21
J2	6	0.03	0.08
J3	17.08	0.512	0.533
J4	13	0.18	0.14
J5	11.06	0.11	0.09

Table 1.1 Power Consumption based on IGTMA algorithm

The scheduled jobs are evaluated along with relevant factors of power consumption optimization aspects towards the execution of individual units. From the Table 1.1 shows, power consumed by executions units are depending on the job size. If minimum, the Good trade off between energy consumption, system load, and the deadline of jobs. All edge servers are evaluated based on Zaman et al.[2] prediction of the mobile user's subsequent location and direction. His suggested approach, COME-UP, uses the weighted sum method to select the top server from the list and then places the incoming job on that server. As LSTM are used for prediction and training instead of complex deep learning models, COME-UP has become a lightweight technique. The fundamental flaw with this system is that there is no mechanism for virtual server relocation in the event of server overload or failure. The central processing units (CPUs) endeavors 80% of the electrical energy in edge servers compared to other resources. Furthermore, when operating at full speed, idle CPUs account for 70% of the overall energy utilized by the server. As a result, an increase in CPU use is proportional to energy consumption (Table 1.2).

Jobs	Job Size (KB)	Execution time(mSec)	Power Consumption(watt)
J1	12.03	0.128	0.29
J2	6	0.001	0.12
J3	17.08	0.161	0.611
J4	13	0.137	0.39
J5	11.06	0.102	0.20

Table 1.2 Power Consumption based on COME-UP algorithm

The above Table 1.2 illustrate, power consumption variation based on its CPU processing time of incoming task units. In the present exploration, the Grey Wolf Optimizer (GWO) was used to minimize the monthly energy consumption of an office structure in Seattle rainfall conditions. The GWO [9] is a meta- heuristic optimization system and the optimization system was enciphered and coupled with the Energy Plus canons to perform the structure optimization task. The impact of algorithm settings on the optimization performance of GWO was explored, and it was set up that GWO could give the stylish performance by using 40 wolfs. The optimized results of GWO were compared with other optimization algorithms in the literature, and it was set up that the GWO could lead to an excellent optimum result efficiently. The results showed that it could give an excellent library of non-dominant optimum results. is robust to the state changes in the MEC terrain (Table 1.3).

Jobs	Job Size (KB)	Execution time(mSec)	Power Consumption(watt)
J1	12.03	0.311	0.09
J2	6	0.192	0.03
J3	17.08	0.389	0.438
J4	13	0.349	0.324
J5	11.06	0.219	0.14

Table 1.3 Power Consumption based on GWO algorithm

The above Table 1.3 exhibits the power consumption based on job size and execution time by CPU fetch cycles.

3. PERFORMANCE EVALUATION

The mentioned techniques still have some performance and flexibility issues, though. Additionally, due to the algorithm's complexity, large-scale network scenarios are not appropriate. Consequently, a task offloading method that is effective is created for mobile-edge computing (MEC). It is common knowledge that the base stations in the majority of wireless networks operate in multichannel mode.

The transmission rate of the data will be severely impacted by inter active communication interference if high number of cell phone device users simultaneously select the same wireless channel to carry out task offloading. This will further increase task completion delays and mobile device energy consumption. Due to the mentioned consequence are, wireless resource allocation and user offloading decisions are coupled. Therefore, two significant problems must be resolved in order to achieve effective work offloading: Which duties can be offloaded, and which ones should be completed locally? How do I select the best channel to offload work from optimization techniques? An energy-aware task offloading mechanism is created to address the mentioned coupling issues and take into account the mobility of the mobile device in order to overcome the energy-efficient task offloading (EETO) decision issue for mobile-edge cloud computing in the multichannel wireless environment. The following Table (Table 1.4) shows a crystal clear performance analysis of the above mentioned algorithms towards an optimization of energy/power in mobile edge computing devices.

Algorithms	IGTMA	COME-UP	GWO
Job Size(Kb)	12.03	6	17.08
Execution Time(mS)	0.27	0.001	0.389
Power Consumption(Watt)	0.21	0.12	0.438

Table 1.4 Performance Evaluation of MEC algorithms

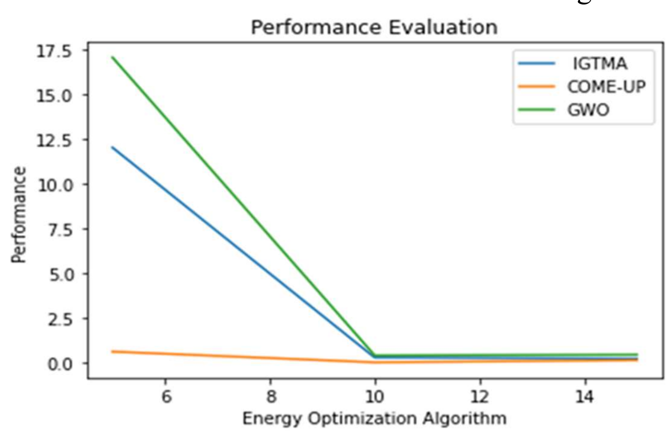

Figure 1.3 Performance Evaluation of MEC algorithms

The analysis purpose, to consider different job size required the execution at mobile edge devices correlated with its execution and power consumption. Even though, the load is in maximum, the GWO is working with proper propositions towards an energy optimization.

4. CONCLUSION

In this research paper, three base methods proposed by researchers for offloading the tasks for saving energy were discussed. The performance comparative analysis reveal that the current job offloading techniques used in mobile edge computing is insufficient to significantly increase the system's energy efficiency with standard computational factors. The main drawback of performance evaluation is the significant transmission latency between the mobile device and conventional cloud servers. For mobile apps, the excessively long latency caused by the extensive propagation distance between the mobile device and the faraway cloud data center is undesirable. In spite of this, the performance will be maintained in order to optimize the energy carry over with Grey Wolf Optimization algorithm with an energy saving mechanism in MEC.

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