Journal of Information Systems Engineering and Management
2025, 10(13s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Hierarchical Fuzzy Clustering and Sleep Scheduling for Load Balancing in 5G-IoT Networks

[1]T.S.Rashad and [2]A.Ch.Sudhir

1 Research Scholar, Dept of EECE, GST, GITAM (Deemed to be University),Visakhapatnam,A.P,India. 1rashadphd@gmail.com

2Associate Professor, Dept. Of EECE, GST,GITAM (Deemed to be University), Visakhapatnam,A.P,India. 2camanapu@gitam.edu

ARTICLE INFO

Received: 01 Dec 2024

Revised: 15 Jan 2025

Accepted: 30 Jan 2025

ABSTRACT

Introduction: Small cells have been added to Fifth Generation (5G) networks for handling the increasing demands for ubiquitous service and mobile traffic. Furthermore, it makes it possible for mobile broadband technology to be used everywhere to locate Internet of Things (IoT) applications. Existing research suggests strategies to maintain network segment distribution to various applications effectively.

Objectives: The major objective of this work is to balance the loads among the cells in IoT-5G networks.

Methods: This paper proposes Hierarchical Fuzzy clustering and sleep scheduling (HFC-SS) technique for load balancing in 5G-IoT networks. This approach creates and groups sub-segments for every network segment for handling IoTs applications with various resource demands. The hierarchical Fuzzy clustering techniques is applied for sub-splitting based on a cumulative rank of Quality of service (QoS) metrics. Then, an adaptive sleep scheduling technique is applied on every small cell base station (SBS) depending on its load. The overloaded traffic may be sent to the Macro cell under the load balancing policy (LBP), when the mean load of any SBS surpasses the Macrocell's load.

Results: The validation of simulation results against analytical results demonstrates that the proposed techniques provide maximum delivery ratio and power efficiency with minimized energy usage and drop rate of SBSs.

Conclusions: The proposed HTC-SS technique thus provides efficient load balancing for each SBS.

Keywords: Fifth Generation (5G), Internet of Things (IoT), Hierarchical Fuzzy clustering, Load balancing; Sleep scheduling; Sub-segmentation.

INTRODUCTION

In order to realise the goal of smart cities, IoT is a widespread framework that connects massive amounts of devices and data. The remarkable increase in linked users will result in a massive increase in IoT network traffic. Additionally, the generated traffic could fluctuate regularly [1]. Because IoT devices typically have limited battery life, they are not energy-efficient enough to allow an IoT device to send its content to a large set of users who then try to retrieve it from the IoT device. [2]. It is anticipated that the adoption of IoT would rely on the combination of many different technologies that will make up the 5G and beyond 5G environment. These systems can assist mMTC services in moving towards the so-called cellular IoTs (CIoT) since they provide enormous attention and interference-restricted access [3]. If a cell user detects the loads of nearby cells and chooses the least laden cell, cell loads can become well-accustomed. Although users can connect to many Base Stations (BS) to reduce network congestion, densely positioned small cell networks complicate user association. In the more contemporary 5G networks, load balancing is a useful strategy for easing and balancing traffic among several networks [4].

Target network selection strategy and handoff prediction are used for 5G-IoT networks in the previous paper [5]. Based on user-level variables like security and cost, a fuzzy decision model is utilised to select the target cell [13].

It is not necessary to keep all the idle devices having huge number of assigned tasks, as live. Hence sleep-scheduling technique can be applied over those devices to adaptively change its working mode to sleep or active. When the device is at sleep mode, it will turn off its radio to conserve energy. Similarly in 5G networks, the UEs can turn-off their radios during the sleep period, to save energy. The UE wakes up and sleeps with specific patterns at pre-defined time periods [19][20].

Objectives: Previous research suggests strategies to maintain the efficient allocation of network segments to different applications. In Machine Learning-Based Network Sub-Slicing Framework [7], sub-segments are formed for each network segment and grouped. But IoT devices should be grouped efficiently based on their common QoS requirements or services. Dynamic sleep-scheduling techniques should designed for each SBS , depending the seize of its cell load.

The main objective of our research effort is to design LBP to satisfy the diverse 5G-IoT applications with different QoS requirements, depending on the problem statement. As a follow-up to this study, we therefore propose to design an adaptive sleep scheduling and network segmentation-based load balancing strategy for 5G-IoT networks.

This research develops an adaptive sleep scheduling and network segmentation-based load balancing method for 5G-IoT networks.

RELATED WORKS

A machine learning (ML) based network sub-slicing architecture has been proposed by Sushil Kumar Singh et al. [7] to handle load balancing difficulties in 5G networks. Each logical slice in this work is split into a virtual sub-slice of sources. As required, each sub-slice gives the program with various ordered resources. A traffic engineering (TE) policy has been proposed by KaigeQu et al. [8] for effective resource maintenance between slices in order to lessen congestion and prevent the ensuing degradation of QoS. The proposed TE framework can benefit from the deployment of hierarchical Software Defined Network (SDN) controllers in both the infrastructure and client domains in conjunction with NFV architecture.

The operational possibilities for the SBS utilizing the dynamic sleep mode in relation to its observed load level have been well outlined by Xiao et al. [9]. For their designed sleep modes, the success probability expressions for coverage are found and energy savings are given, dependent on the success probability limitation. The theory of MDPs has been applied by Kir et al. [10] to enhance a near-best state based policy, where energy is lowered for a biassed sum of the act and energy. They specifically employed the first phase of the familiar policy iteration technique to determine the marginal future cost of accumulating arrivals in any type of cell, for each arrival.

The data-driven resource management framework (BEHAVE) has been designed by AlQerm et al. [14] which distributes the edge resources to IoT devices in an intelligent and equitable manner considering their resource demand behaviour. Additionally, they have introduced DeepEdge, a cutting-edge two-stage deep reinforcement learning technique.

PROPOSED METHODOLOGY

Overview

This paper proposes hierarchical Fuzzy clustering and adaptive sleep scheduling (HFC-ASS) technique for load balancing in 5G-IoT networks. The proposed method creates distinct network segments to handle different QoS requirements. Initially, the collection of IoT devices is skilfully arranged according to their common demands or services. Cluster IDs are allotted based on similar types of application resources. The three primary QoS factors—latency, power efficiency, and average traffic load—are taken into account during segmentation. These QoS variables are then used to estimate a cumulative rank for each section. This cumulative rank of all segments is used to define the dynamic sleep mode for each SBS in the following phase. When an SBS's average load becomes above that of the Macrocell in the LBP of SBS, the overloaded traffic may be transferred to the Macrocell.

Network Segmentation and Network Sub-segmentation (NSS)

In order to use network services in a 5G environment that is sustainable, network segmentation is an essential strategy. The network segmentation architecture enables a node to provide services to specific users based on their needs. Depending on their preferences, these users provide different services. Network Functions Virtualization (NFV) is used to achieve network segmentation [7]. The NSS method splits the parent network segment into sub-segments to perform load balancing. The steps in the suggested NSS framework for 5G networks are shown in this section. It has the following unique components:

(1) Service attributes selection explains the method for selecting the attributes in an IoT-5G setup based on the capabilities of intelligent apps. During the device attribute selection process, QoS criteria developed are used to rank IoT devices. The characteristics that score lowest are removed. Finally, the service attributes of all IoT devices for NSS are obtained in the descending order .

(2) At the IoT layer, grouping and sub-segmentation are connected. For grouping and sub-segmentation, the HFC algorithm is employed. In many IoT applications, each sub-segment is applied to particular sub services. The HFC method is used to build sub-segments, and the cluster is assigned depending on the cumulative rank of IoT devices.

Cumulative Rank Estimation

Each cell's IoT devices are assigned a cumulative rank, depending on the mean cell load, mean battery power and transmission delay. The data rate D is used to express the cell load. In a collection K_i, the load L for a traffic request r can be obtained by

$$L_i^r = D(r)$$

The aggregate load for all the traffic demands in K_i at time instant t can be subsequently,

$$L_i(t) = \sum_{r=1}^{R} L_i^r \quad (1)$$

The average residual battery power of every node (P_{rb}) after the data communication is assessed by the following equation.

$$P_{rb} = [P_{bi} - (P_{tx} + P_{rx})] \quad (2)$$

Where Pb_i is the initial battery power, P_{tx} is the transmit power and P_{rx} is the receiving battery power.

Let F denotes the transmission delay. For a user U_j in the cell K_i, the cumulative rank C is provided by

$$C^i_j = (w_1 . L)\,(w_2 . F) / (w_3 . P_{rb}) \quad (3)$$

3.3.3Attribute Selection and Ranking

The attributes of the IoT devices, BS id, the load of traffic request D(r), device id, cell id, PW and delay F are gathered. Assume S as the subset of attributes, where S = [1, 2,.......n] and $B = \phi$ as the rank list. The following algorithm illustrates the process of choosing and ranking the attributes:

Algorithm-1: Attributes selection and ranking

---

1. Sort attributes until $S = \phi$

2. Limit to indices of good attribute: $A_0 = A(:, s)$

3. Calculate latency F, load factor L and battery power P_{rb} using Eq. (1) and (2)

4. Calculate the weight values w_1, w_2 and w_3

5. Estimate the cumulative rank C by applying Eq.(3)

6. Select the attributes with the minimum rank

$$F = \arg_k \min G_k$$

7 Stop this aspect by applying the least ranking principle, so that $LB = s(1: f-1, f+1, length(s))$

Adaptive Sleep Scheduling (ASS) for SBS

Every SBS supports load-aware dynamic sleep mode, instead of randomly turning off SBSs. The active probability for an SBS_k with load level L_k is $A(L_k)$, while the sleep probability is $(1-A(L_k))$. The function increases until the load level L_i crosses the load threshold L_{th},.

Therefore T_{SLEEP} is calculated by

$$T_{SLEEP} = 1 - A(L_k) \tag{4}$$

L_{th} is assumed to be the same across all SBSs. It is assumed that the SBS has the ability to automatically determine its load level in relation to traffic demand within a specific time frame.

Design of Load Balancing Policy (LBP)

Let as assume a LBP P_{LB} calculated by the vector v = $(v_1,\ldots\ldots v_n)$, in which every term v_n provides the probability of assigning the arriving request to the small cell C_n and $(1-v_n)$ provides the probability to Macrocell H_M. According to their cell loads, the small cells, $C_1,\ldots\ldots C_N$, are arranged in the descending order. $H_1 > H_2 \ldots\ldots > H_N$. For all C_i, in which the value of previous load is below the value of the load of H_M, no traffic can be moved to H_M, that is, the resultant $P_{LB} = 1$ Therefore, K^* indicates the maximum index of C_i , from where the load can be moved to H_M,

$$k^* = \{\max k = 1,\ldots\ldots, N : H_k > H_M\} \tag{5}$$

Algorithm:-4 LBP

1.PLB = $\{V_1,\ldots\ldots V_n\}$

2. Sort $\{C_k$, k=1,..N$\}$such that $H_1 > H_2 \ldots\ldots > H_N$

3. For each C_k

4.If $H_k < H_M$, then

5. $P_{LB}(k) = V_k = 1$

6. Else if If$H_k >= H_M$,then

7. k* = k

8. break

9. End if

8. End For

9. For each C_j, j=k*, ...N (k* > k)

10.$P_{LB}(j)$ = Move $H_j$to C_M

11. End For

12. Stop

Simulation Results

The Machine Learning based Network Subslicing Framework (MLBNSF) [7] and Sleep-Scheduling and Joint Computation-Communication Resource Allocation (SS-JCC-RA) [20] are compared with the proposed HFC-ASS technique, which is simulated in NS2.In the experiments, the performance parameters power efficiency, packet drop, computing overhead, delivery ratio and energy consumption are examined. The simulation setup consists of 6 macro cells and 12 small cells in a region of 500x500m. The cell range of macro and small cells are 5km and 25m respectively.

RESULTS AND DISCUSSION

This section presents the simulation results of all the 3 techniques for varying the laod of each SBS from 10 Mb to 20Mb.. Figure 1 depicts the energy consumption values for all the 3 techniques.

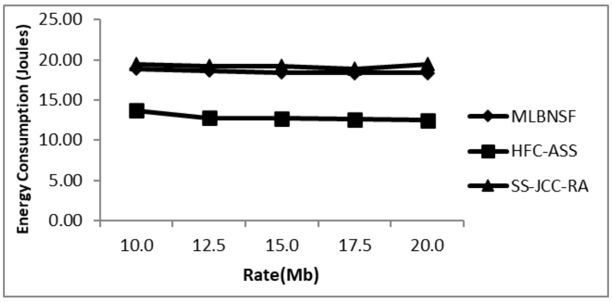

Figure 1 Energy consumption for varying Rate

Figure 1 displays the mean energy consumption, measured by varying the traffic rate. HFC-ASS uses 30% less energy than the MLBNSF procedure and 33% less energy than SS-JCC-RA because it offers adaptive sleep scheduling for tiny cells.

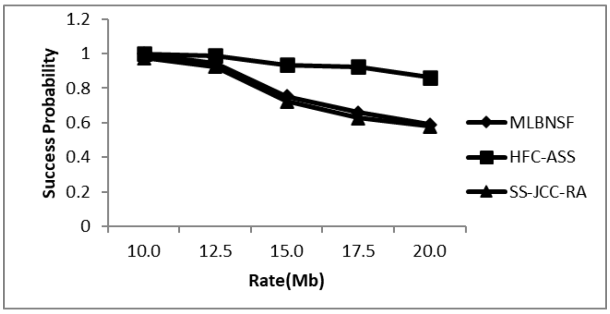

Figure 2 Delivery ratio for varying Rate

Figure 2 displays the data delivery ratio obtained at different rates. HFC-ASS has a success probability that is 17% greater than MLBNSF and 19% higher than SS-JCC-RA because it takes into account the cumulative rank of devices calculated from the load.

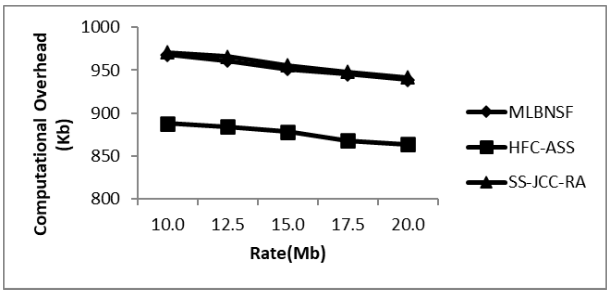

Figure 3 Computational complexity for varying Rate

Figure 3 displays the computational complexity of both approaches at different data rates. HFC-ASS has 8% less overhead than MLBNSF and 8% less than SS-JCC-RA because of the DBSCAN algorithm.

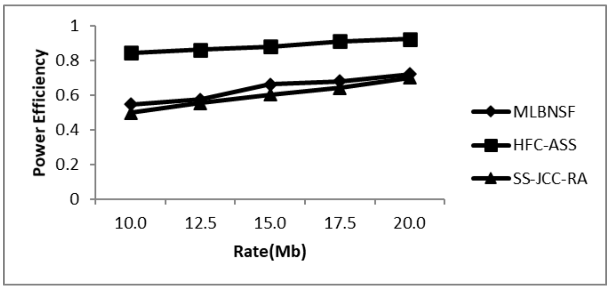

Figure 7 Power Efficiency for varying Rate

Figure 4 displays the average power efficiency for changing the traffic rate. The HFC-ASS scheme is 28% more efficient than the MLBNSF scheme and 32% less efficient than SS-JCC-RA because it offers an adaptive sleep scheduling strategy for tiny cells.

CONCLUSION

In this work, HFC-ASS technique based load balancing method for 5G-IoT networks has bee proposed. According to this method, sub-segments are created and organised for each network segment in order to handle IoT applications with various QoS needs. Depending on the cumulativce combined rank of QoS metrics, the HFC technique is utilised for sub-segmentation and grouping. Adaptive dynamic sleep scheduling is implemented by each SBS in the subsequent phase, contingent on its load level. According to the SBS LBP, overloaded traffic may be forwarded to the Macrocell when the mean load of any SBS surpasses the Macrocell's load. The MLBNSF and SS-JCC-RA approaches are contrasted with the suggested HFC-ASS strategy, which is put into practise in NS2. The validation of simulation results against analytical results demonstrates that, in comparison to existing methodologies, the proposed HFCoASS technique provides maximum delivery ratio and power efficiency with minimum energy utilization and packet drops.

REFERENCES

[1] Mostafa Mouawad , Zbigniew Dziong and Ahmed El-Ashmawy, "Load Balancing in 5G C-RAN based on dynamic BBU-RRH Mapping Supporting IoT Communications", IEEE Global Conference on Internet of Things (GCIoT), 2018.

[2] Xiang Sun and Nirwan Ansari, "Traffic Load Balancing among Brokers at the IoT Application Layer", IEEE Transactions on Network and Service Management, vol. 15, no. 1,,pp. 489-502, March 2018.

[3] Pol Serra i Lid´on,Giuseppe Caso, "Two-tier Architecture for NB-IoT: Improving Coverage and Load Balancing", IEEE, 2019.

[4] Christos Tsirakis, Panagiotis Matzoros, Petros Sioutis and George Agapiou, "Load balancing in 5G Networks", MATEC Web of Conferences, Vol-125,2017.

[5] Rashad.T.S.and A.Ch. Sudhir," Fuzzy-Neural based Cost Effective Handover Prediction Technique for 5G-IoT networks", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Volume-9 Issue-2S3, December 2019, ISSN: 2278-3075

[6] Saniya Zahoor and Roohie Naaz Mir, "Resource management in pervasive Internet of Things: A survey", Elsevier,Journal of King Saud University – Computer and Information Sciences 33 (2021) 921–935, 2021

[7] Jia-Ming Liang,Member, Jen-Jee Chen,Member, Hung-Hsin Cheng and Yu-Chee Tseng,"An Energy-Efficient Sleep Scheduling With QoS Consideration in 3GPP LTE-Advanced Networks for Internet of Things", IEEE Journal on Emerging and Selected Topics In Circuits and Systems, Vol. 3, No. 1, March 2013

[8] KaigeQu,WeihuaZhuang,QiangYe,Xu Li, and Jaya Rao, "Traffic Engineering for Service-Oriented 5G Networks with SDN-NFV Integration", IEEE,2018.

[9] Sushil Kumar Singh ,Mikail Mohammed Salim, Jeonghun Cha , Yi Pan and Jong Hyuk Park, "Machine Learning-Based Network Sub-Slicing Framework in a Sustainable 5G Environment", Sustainability,Vol-12, 2020.

[10] KaigeQu,WeihuaZhuang,QiangYe,Xu Li, and Jaya Rao, "Traffic Engineering for Service-Oriented 5G Networks with SDN-NFV Integration", IEEE,2018.

[11] Zhu Xiao, Shuangchun Li, XiaochunChen,Dong Wang and Wenjie Chen, "A Load-Balancing Energy Consumption Minimization Scheme in 5G Heterogeneous Small Cell Wireless Networks Under Coverage

Probability Analysis", International Journal of Pattern Recognition and Artificial Intelligence,Vol. 31, No. 7,2017.
[12] Misikir Eyob Gebrehiwot, Pasi Lassila and Samuli Aalto, "Dynamic load balancing in 5G HetNets for optimal performance-energy tradeoff", IEEE,IFIP, 2018.
[13] Ismail AlQerm, Jianyu Wang, Jianli Pan and Yuanni Liuy, "BEHAVE: Behavior-Aware, Intelligent and Fair Resource Management for Heterogeneous Edge-IoT Systems", IEEE Transactions on Mobile Computing, 2021
[14] Ismail AlQerm and Jianli Pan,(2021) "DeepEdge: A New QoE-based Resource Allocation Framework Using Deep Reinforcement Learning for Future Heterogeneous Edge-IoT Applications", IEEE.