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Efficient Radio Resource Optimization Schemes by Exploring Fog-Based Internet of Things (EROS F-IoT)

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Abstract: Nowadays Cloud-enabled Internet-of-Things (IoT) gaining a lot of attention towards providing real-life solutions. Additionally, the inclusion of fog components in the cloud enabled IoT network brings cloud services to the edge devices of the networks. This leads the cloud enabled IoT network to the next level which is any time anywhere service. Due to the limited resources, the heterogeneous and massive today's fog based IoT networks face efficient resource utilization challenges. Many recent articles are present in the literature on resource allocation in cloud assisted IoT networks but this research are mostly based on either computational resource allocation or radio resource allocation. In this study, we have examined the radio resource allocation schemes for fog based IoT networks. Also, many research articles are present in the literature on radio resource allocation however, they only consider overlay resource allocation i.e., they have examined the performance of dedicated resources for the IoT networks. In order to efficiently utilize limited radio resources, they can be reused by IoT devices. Additionally, these schemes don't consider the consequence of the interference generated from the CUs. In this study, we have presented a radio resource allotment scheme to handle different QoS requirements of fog based IoT networks. First. We formulated an optimization problem for diverse QoS demands of IoT devices with different capabilities next, we have recommended a two-step radio resource allocation scheme by optimal allocation of channels and transmit power. The simulation results portray that our proposed scheme enhances the performance of considered QoS parameters compared with other related baseline methods.

Keywords: *Fog-based networks (FBN), Internet of Things (IoT); radio resource allocation; ultra-reliable low latency communications (URLLC); enhanced mobile broadband (eMBB); resource allocation.*

1. Introduction

Literature forecasts that in 2025, fifty billion IoT devices will be connected to the internet [1]. The advancement of IoT applications in different uses in today's world, i.e., industrial applications, health care, automation, etc accelerated the growth of the socio-economic sector [2]. Any smart device can communicate directly with another by enabling cloud assisted IoT technology. The exponential growth of IoT applications in the real world imposes new challenges in traditional centralized cloud enabled IoT networks, such as high latency, limited processing, link failure, and so on [3]. Nowadays to manage the objections mentioned above, a newly added technology called fog computing imports the conventional centralized cloud services closer to the edge devices, i.e. IoT networks. Fog computing enables the features of local processing and storage, which required low latency and computations [4-6].

The term "fog computing" is first introduced by Cisco in 2012 [7]. A new technology is presented, called fog computing, with many compensation packages in the field of cloud enabled IoT applications. Like cloud computing, fog computing also provides processing and storage as a service with the added benefit of speedy responses. Processing and storage are performed locally in fog computing, which differentiates it from cloud computing. However, both the cloud and fog are designed to provide storage, processing, and network resources [8].

The prominent objective of any IoT network is to provide the required QoS to the end-user. The required QoS can be provided by the optimal allocation of the resources of the networks [9-11]. However, the edge device can utilize both the licensed spectrum and unlicensed spectrum depending on the availability and requirement of the IoT applications [12]. The heterogeneous environment of the IoT network leads resource allocation to be more challenging. Different IoT applications need distinct QoS requirements, for a better understanding of the readers, as we have depicted in Table 1.

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Table 1: Different IOT applications requirement

Application	Delay	Data rate, (Mbps)	RER
RT Data	0.001 to 1	≤ 10	0
Image	1	2^-10	2^-4
Audio	0.25	0.064	≤ 10^-1
Video	0.25	100	10^-2

The real-time data applications demand very less delay along with almost nil BER and the image, video and audio applications need acceptable delay and BER rate. The two most used IoT application services are Ultra-Reliable Low Latency Communications (URLLC) service type [13-14] and enhanced Mobile Broadband (eMBB) service type applications in today's IoT networks. The URLLC service requires decent BER with less delay where the eMBB service demands a high data rate. So the allocation of the network resource has to be capable to manage these different types of requirements.

Although, many resource management schemes [15] are present in the literature these schemes are mainly focused on task scheduling or computation distribution. Whereas the resource allocation has to be considered both the required QoS parameters and the priority of the service type also in any IoT network. Thus, the optimal allocation of a radio resource (Channels and power) along with the service priority has to be well investigated as well.

The above-mentioned requirements of resource allocation schemes motivate us to propose network resource allocation schemes that have to be capable to address both the prime requirements of QoS parameters and the service priority of any IoT network.

In this study, a resource allocation scheme is proposed to optimally allocate the demanded QoS requirements with the service priority of different IoT applications. Additionally, we have proposed a transmit power allotment strategy to optimize the considered QoS parameters of IoT users. The outstanding improvement of this study is presented as:

1.1 Contribution

The prominent contribution of this paper is summarized as:

I. We propose a radio resource allocation scheme for the considered fog based IoT network. This scheme is based on the proposed Interference dominant areas (IDA) algorithm to allocate the optimal resources to both the users (CUs, and IoT). The state-of-the-art is that we have considered a CUs underlay fog based IoT network where the IoT devices reuse the radio resources of CUs.

II. A PSO-enabled power allotment strategy is proposed to optimal allocation of power to cellular users and IoT devices. The prime objective of this method is to enhance the network throughput of the overall cell devices. Also, this scheme minimizes the co-channel interference along with the BER rate as well.

III. We have conducted an extensive simulation to analyze our proposed scheme with some baseline methods. The outcome of the simulation depicts that the presented scheme outperforms supplementary correlate schemes.

The rest of this paper is as follows: wherein section 2 the related work of this study is presented and in section 3 we have presented the system model of this study. Section 4 and Section 5 present the problem formulation of this study and the proposed radio resource and power allotment blueprint sequentially. An extensive simulation of this study is done, and the presenter is in section 6. Further, we conclude our study in section 7.

2. Related Work

IoT is becoming a part of daily life in recent years by its wide area of applications like cell phones, smart health care, smart agriculture, climate monitoring, etc [16]. To handle the massive amounts of data produced by the different IoT devices many research articles are proposed to handle different demands. In [17], the authors proposed a joint channel and computing resource allotment scheme for fog based IoT networks where they have analyzed the performance of different QoS parameters of the IoT networks. The proposed scheme follows the student project allocation (SPA) game model for resource allocation. In [18] authors proposed a service-oriented radio channel allotment scheme for fog-based IoT networks. The proposed scheme allocates the job resources based on the suggested graph partitions algorithm where they also analyzed the QoS parameters of the considered system. In [19] authors proposed a network resource allocation along with user selection for the fog based IoT networks. They have implied a two-way matching game model for the user selection and network resource allocations. In [20], the authors proposed a joint radio resource allocation and computation allocation to the fog based IoT networks. They have considered a single fog device in the cell with multiple CUs where the network resource of CUs can be reused by the fog networks. In [21] the authors examine the combined fog-cloud-based networks where they propose a computation offloading scheme. To indicate the heterogeneous network, they have considered micro cell-based fog networks where a robust cloud server indicates the massiveness of the networks. In [22] and [23], the authors examine the energy efficiency of the NOMA-based cloud IoT networks. They have analyzed the downlink performance of the considered networks. In [24] the authors proposed a QoS aware resource optimization with the constraint of the non-interchangeable resource allocation for the cloud assisted IoT networks. They have considered single-cell heterogeneous networks where different IoT devices are uniformly deployed with different QoS requirements of the whole cell. In [25] the authors proposed a QoS-based resource allocation scheme in fog-based IoT networks. The proposed scheme is designed to handle both the user's and network's requirements such as in users' point of view they demand high data rate whereas a network requires load balancing along with the utilization of the resources. In [26] the authors proposed a centralized resource allocation scheme for fog based IoT networks. They have formulated a utility function for pairing the IoT users which is based on Irving's stable roommate methods. In [27] the authors proposed a Stackelberg game-based resource allocation scheme in fog based IoT network. The proposed scheme is hierarchical in nature where they have modeled the resource allocation problem as a leader-follower concept. In [28] authors proposed a resource allocation scheme for D2D enabled fog based IoT networks where they have formulated an optimization problem for the allocation of different types of resources. In this study, they have designed the many to many matching game models for heterogeneous resource demands.

3. System Model

In this section, we have demonstrated our considered system model as depicted in figure 1. The mathematical estimation of this study is expressed as; Where the C represents the set of total cellular users deployed uniformly under the coverage region of an eNB. The eNB has K number of downlink sub-channels for the allocation of CUs and is denoted as a set of K = {1……………K}. Here the C = {1.........CU} denotes the set of CUs presented in the cell. To demonstrate the fog device, we have considered the R number of fog access points (FP) which is represented as a set of R = {1........................R} and, each FP have its associated IoT devices with different QoS parameter like mobile phone, laptop, tab, etc. The set of IoT devices in each FP is denoted as a set of I = {1.......I}. Where M number of QoS parameters are deployed in FP to support different users and, represented as M = {1...............M}. The S number of different services are provided by the IoT service providers and denoted as S = {1..................S}. We have denoted a vector $v_{I, s}^m$ to denote the different weights of different QoS parameters. Where the individual weight vector $w_{s,d}$ indicates the weight of one of the service type QoS parameters.

In this study, we have assumed eNB acts as a fog network coordinator (FN) which is capable to provide the IoT service to the edge IoT devices. In this study, we have studied two major types of IoT services i.e., eMBB and URLLC. Also, the different QoS service parameters have different weights to differentiate service types, in eMBB service type required the high throughput, and the URLLC service type required the tolerable delay along with a low bit error rate (BER). The assumption is taken here the FN is capable to execute various service types concurrently. Additionally, the IoT devices are capable to run the different types of IoT applications, and the FP act as a serving gateway to access the cloud services. It means that each IoT device accesses the service of the cloud via FP where FP acts as a mediator between the FN/eNB and edge IoT devices. In this scenario, the IoT devices reuse the resources of the primary CUs which have to be optimally allocated to the FN via FP. After that, the FP will update the status of allocated resources to the FN to ensure that the only legitimate IoT device can access the resources.

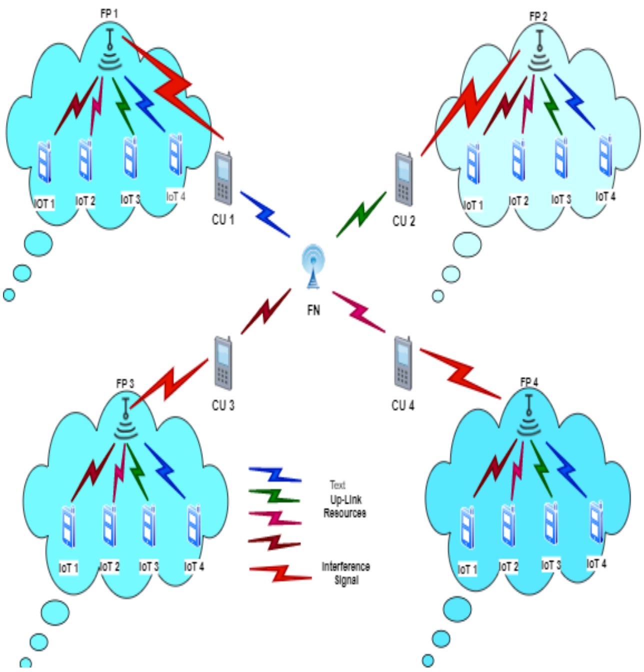

Fig 1. System Model

3.1. Channel allocation:

Channel allocation: Let us consider a scenario where a ith, IoT device wants to access any cloud service of any FP. At that time the FP forwards the request to the FN and FN will allocate the kth sub-channel of any jht CUs to reuse the IoT device. In this case, the SINR of the ith IoT devices and the jth CUs can be calculated as:

$$SINR_{I_i}^k = \frac{P_{I_i} g_{I_i - FP}}{\sigma^2 + Int_{cu_j}} \tag{1}$$

$$SINR_{cu_j}^k = \frac{P_{cu_j} g_{cu_j - FN}}{\sigma^2 + Int_{I_i}} \tag{2}$$

Where in Eq. (1) and (2) the $\boldsymbol{P_{I_i}}$ and, $\boldsymbol{P_{cu_i}}$ represents the transmit power of the ith IoT devices and jth CUs respectively. The $\boldsymbol{g_{cu_i-FN}}$ and $\boldsymbol{g_{I_i-FP}}$ denotes the channel capacity of channel gain between the CU to FN and IoT to FP. And the Ii indicate the interference value from IoT devices in the kth sub channel which is represented as $Int_{I_i} = P_{I_i} g_{I_i-cu_i}$ also the

I_{cu} indicate the interference value from CUs in the kth sub channel and denoted as $Int_{cu_j} = P_{cu_j} g_{cu_j-I_i}$. The σ^2

indicate the thermal noise power. Additionally the channel capacity of the ith IoT device and jth CUs can be calculated by Shannon's formula [29] which is denoted as:

$$CC_{I_i}^k = w_{i,c}^k log_2\left(1 + \boldsymbol{SINR_{I_i}^k}\right) \quad (3)$$

$$CC_{cu_j}^k = w_{i,c}^k log_2\left(1 + \boldsymbol{SINR_{cu_j}^k}\right) \quad (4)$$

Here $w_{i,c}^K$ a indicating variable which indicates that the allocated bandwidth to both the IoT device and CUs is the subchannel of $k \in K$ and the $I_i \in A_i$.

3.2 Bit error rate computation:

The data transfer in cellular communication and IoT communication can be falsified even if the interference is inconsequential. This can be possible if the BER is less than the threshold limit. The spectral efficiency of the transmit signal can be mapped by bit error rate as

$$E_{LICU}^k = \frac{data\ rate}{allocated\ bandwidth}$$

by Eq. (3) and (4). The BER of the ith IoT device and the jth CUs can be calculated by [29].

$$BER_{I_i}^k = \begin{cases} 0.2 * e^{\frac{\frac{E_{I_i}^k}{\sigma^2 + I_{cu_j}}}{\log(t)-1}}, & if\ \frac{E_{I_i}^k}{\sigma^2 + I_{cu_j}} \geq T_m \\ 1, Otherwise \end{cases} \text{-(5)}$$

$$BER_{cu_j}^k = \begin{cases} 0.2 * e^{\frac{\frac{E_{cu_j}^k}{\sigma^2 + I_{I_i}}}{\log(t)-1}}, & if\ \frac{E_{cu_j}^k}{\sigma^2 + I_{I_i}} \geq T_m \\ 1, Otherwise \end{cases} \text{-(6)}$$

In Eq. (5) and (6) the $\frac{E_{I_i}^k}{\sigma^2}$, $\frac{E_{cuj}^k}{\sigma^2}$ indicate the ratio between spectral efficiency verses thermal nose power and the T_m and (t) threshold modulation value and modulation indicator sequentially.

3.3 Quality of Service maximizations:

If FN allocates the CUs downlink sub channels to reuse the IoT devices then the maximation function of the QoS parameters (CC and BER in this study) is expressed as:

$$M_{QoS} = \left(v_{I,s}^{m1}\right) * \left(CC_{I_i}^k + CC_{cu_j}^k\right) * \left(v_{I,s}^{m2}\right) * \left(\left(1 - BER_{I_i}^k\right) + \left(1 - BER_{cu_j}^k\right)\right)$$

-(7)

In Eq. (7) the $v_{I,s}^{m1}$,, and $v_{I,s}^{m2}$ denote the weights of different QoS parameters.

4. Problem Establishment

In this section, we have elaborated on the problem formulation of this study. The prominent objective of this study is to maximize the two QoS parameters i.e., data rate and, BED of the CUs and IoT devices. The mathematical present this our objective function is formulated as:

$$\max_{\alpha_{I,k}\beta_{I,r}w_{i,c}^k} \sum_{e\epsilon R} \sum_{i\epsilon I} \sum_{k\epsilon K} \alpha_{I,k}\beta_{I,r} M_{QoS} \quad \text{- (8)}$$

$$\sum_{cu\epsilon CU} \sum_{i\epsilon I} \sum_{k\epsilon K} \alpha_{I,k}\beta_{I,r}\, w_{i,c}^k \leq w_{max}^k, i \in I, cu \in CU, r\epsilon R \quad \text{(c1)}$$

$$\alpha_{I,k}\beta_{I,r} CC_{I_i}^k \geq CC_{I,QoS}^k \forall\ i \in I, r\epsilon R, k\epsilon K \quad \text{(c2)}$$

$$\alpha_{I,k}\beta_{I,r} CC_{cu_j}^k \geq CC_{cu,QoS}^k, \forall\ cu \in CU, r\epsilon R, k\epsilon K \quad \text{(c3)}$$

$$BER_{I_i}^k \leq BER_{I_{max}}^k, i \in I, r\epsilon R \quad \text{(c4)}$$

$$BER_{cu_j}^k \leq BER_{cu_{max}}^k,, \forall\ cu \in CU, k\epsilon K \quad \text{(c5)}$$

$$\alpha_{I,k} \sum_{m\in M} v_{I,s}^m \leq 1, \forall\ i \in I, k\epsilon K \quad \text{(c6)}$$

$$\sum_{k\in K} \quad \alpha_{I,k} \leq 1,, \forall\ cu \in CU,\ r\epsilon R \quad \text{(c7)}$$

$$\sum_{i\in I} \beta_{I,r} \leq Q_r\ \forall\ r \in R \quad \text{(c8)}$$

$$\sum_{r\in R} \beta_{I,r} \leq 1\ \forall\ i \in I \quad \text{(c9)}$$

The objective of this study is expressed as a gain function of the QoS parameters which is described in Eq. (9). Where constraint (C1) indicates that the allocated bandwidth has to be always less than the maximum bandwidth. Constraints (C2), and (C3) make sure that the data rate of the IoT devices and CUs is always maintained above the threshold limit of the users. The constraint (C4), and (C5) is responsible for maintaining the BER rate, which has to be always greater than the threshold value for all the CUs and IoT devices. The constraint (C6) represents the weight of the desired service type of the IoT devices and in, constraint (C7) represents that an IoT is allocated to the sub-channel k under a fog device. The constraint (C8) denotes that every FP can be associated with at most **Ai** number of IoT devices where the **Ai <= K.**. And the constraint (C9) indicate that any IoT device can be associated with only one FP. The variable $\boldsymbol{\alpha_{I,k}}$ and $\boldsymbol{\beta_{I,r}}$ present in constraint (C7) and (C9) are the binary variable which is expressed as:

$$\alpha_{I,k} = \begin{cases} 1, If\ I\ is\ allocated\ by\ sub-channel\ k \\ 0, Otherwise \end{cases} \quad \text{-(9)}$$

$$\beta_{I,r} = \begin{cases} 1, If\ i\ is\ related\ ot\ r \\ 0, Otherwise \end{cases} \quad \text{-(10)}$$

The objective function presented in eq. (8) with different QoS parameter constraints (C1) to (C9) lead to an NP-hard problem that is hard to solve in polynomial time. To propose a more robust solution we have sub divided the QoS awaired resource allocation problem into two sub problems. In the next section, we have proposed a solution for this maximization problem by optimally allocation the channels and transmitting power to both the CUs and IoT users.

5. Proposed Schemes

This section depicted the radio resource allotment scheme where two-step sub-channel allotment and power allotment proposals in the following subsections. Sub-channel allocation is intended to maximize the throughput of both the CUs and IoT Devices. Additionally, the power allotment proposals are developed to improve the transmit power utilization of both devices to limit the co-channel interference generated by the users (CUs, and IoT).

5.1. QoS aware sub-channel allocation scheme:

In this sub-section, we have presented the gradual process of our QoS-aware sub-channel allocation scheme. In this scheme, the interference-dominated areas (IDA) of all the CUs and the IoT devices are determined by the FN. Here IoT network refers to a set of one FP and multiple IoT devices as depicted in figure-1. Thereafter the FN will allocate the appropriate sub-channels to the IoT networks. First, we have driven the expression for IDA for CUs and the IoT networks. After that, the FN will allocate the sub-channels of CUs to the IoT networks based on the IDA outcome. Here FN assumes that all the CUs and IoT devices transmit data with the maximum allowed transmit power in order to determine the maximum interference. In this scenario, the sub-channel allocation has to be optimized to handle the co-channel interference from different CUs and the IoT users.

Interference-dominated areas of CUs and IoT networks: Let us consider that $\boldsymbol{cu_i}$ is the most effected from the interference generated by a IoT transmitter $\boldsymbol{I_i}$. Here our intention is to manage the IDA to be always less than the threshold limit.

$IDA_{I,QoS}$, **which can be express as:**

$$\frac{Int_i}{\sigma^2} = \frac{P_{I_i} g_{I_i - cu_j}}{\sigma^2} \leq IDA_{I,QoS} \quad \text{-(11)}$$

If we assume that the IoT transmitter I_i transmit with his maximum transmit power, $P_{I_{MAX}}$ then the Int_i can be express as:

$$Int_i = P_{I_{MAX}} * PL(x_1)^{-\alpha_1} \quad \text{-(12)}$$

In Eq. (12) x_1 denote the radius of the IDA_I and the α_1 is denoted as the path loss exponent. Furthermore, if we substitute Eq. (12) into Eq. (11) we ger the radius of IDA_I as:

$$x_1 = \left(\frac{PL * P_{I_{MAX}}}{IDA_{I,QoS} * \sigma^2}\right)^{\frac{1}{-\alpha}} \quad \text{-(13)}$$

Similarly, the IDA_{cu} can be calculated as:

$$\frac{Int_{cu}}{\sigma^2} = \frac{P_{cu_j} g_{cu_j - I_i}}{\sigma^2} \leq IDA_{cu,QoS} \quad \text{-(14)}$$

In Eq. (14) if we replace the CUs transmit power P_{cu_j} into maximum transmit power $P_{cu_{MAX}}$ then the Int_{cuj} can be expressed as:

$$Int_{cu} = P_{cu_{MAX}} * PL(x_2)^{-\alpha_1} \quad \text{-(15)}$$

Where x_2 denote the radius of the IDA_{cu} and which can be derived as:

$$x_2 = \left(\frac{PL * P_{cu_{MAX}}}{IDA_{cu,QoS} * \sigma^2}\right)^{\frac{1}{-\alpha}} \quad \text{-(16)}$$

In Eq. (13) and (16) we can see that the x_1 and, x_2 are mainly dependent on the transmit power of the IoT device $P_{I_{MAX}}$ and, $P_{cu_{MAX}}$ along with the path loss exponent. By obtaining the x_1 and x_2 we can calculate the area of IDAi and IDA_{cu}. Here we can theorize that if any CUs are near to the IDAi can suffer from most severe interference of the

IoT network and, any IoT device near to x_2 will suffer for Sevier interference of CUs. Subsequently, the FN allocates the sub-channel of the CUs to the IoT networks whose IDA is far away from him. The Algorithm 1 presents the step-by-step procedure of the proposed QoS aware sub-channel allocation scheme.

$\boldsymbol{Algorithm\ 1}: QoS\ aware\ sub-channel\ allocation\ scheme.$

$\boldsymbol{Initialization}: CUs\ and\ IoT\ resource\ blocks.$

$Cycle\ T = 0;$

$\boldsymbol{Begin}:$

$\boldsymbol{for}\ each\ CUs\ \boldsymbol{do}:$

$\boldsymbol{CUs}\ prefer\ optimal\ \boldsymbol{RB_N}\ \ after\ observing\ the\ \boldsymbol{IDA_I};$

$\boldsymbol{IoT}\ prefer\ optimal\ \boldsymbol{RB_M}\ \ As\ above\ step\ \boldsymbol{IDA_{cu}}$

$\boldsymbol{T = T + 1};$

$\boldsymbol{end\ for}$

$\boldsymbol{Repetition: As\ far\ as\ all\ CUs\ and\ IoT\ RRB\ unchanged}.$

$\boldsymbol{Obtain}: \boldsymbol{IDA_{IoT,QoS}}$

$\boldsymbol{End}.$

5.2. PSO enabled Power Allocation scheme.

The sub-channel allocation scheme presented in the above-mentioned section is operated in the maximum allowed transmit power of CUs and IoT devices which can also lead to degradation of the BER of the network. To overcome this kind of degradation we have proposed a PSO-based transmit power allotment method here. Here the CUs and IoT devices transmit power are set as the position of the particles as Z_i where i=1….n and now we have formulated the fitness function as the power allocation optimization of the objective function presented in Eq. (8) with respect to the transmit power of the CUs and IoT users.

$$Z_I = (\boldsymbol{P}_{\boldsymbol{I}_1}, \boldsymbol{P}_{\boldsymbol{I}_2}, \dots \dots . \boldsymbol{P}_{\boldsymbol{I}_i}) - (17)$$

$$Z_{cu} = (P_{cu_1}, P_{cu_2}, \dots . P_{cu_j}) \qquad -(18)$$

In this optimization problem, the scope of the particles is set as C+I where C represents the number of CUs, and I represents the number of IoT devices. Thus, the velocity of the particle's CUs, and I is denoted as:

$$v_i^{Pi} = (v_1^{Pi1}, v_2^{Pi2}, v_3^{Pi3}, \dots \dots \dots \dots v_i^{PiI}) \qquad -(19)$$

$$v_i^{Pcu} = (v_1^{Pcu1}, v_2^{Pcu2}, v_3^{Pcu3}, \dots \dots \dots v_i^{Pcuj}) -(20)$$

The velocity of the particles v_i^{Pi} and, v_i^{Pcu} are updated by the following equations.

$$v_i^{Pi+1} = x^{pi} v_i^{Pi} + c_1 r_1 \left(\boldsymbol{P}_{\boldsymbol{I}_1} - Z_{I_i}^{ite\_i}\right) + c_2 r_2 \left(\boldsymbol{P}_{\boldsymbol{I}_g} - Z_{I_i}^{ite\_i}\right) \qquad -(21)$$

$$v_j^{Pcu+1} = x^{pcu} v_i^{Pcu} + c_1 r_1 \left(P_{cu_1} - Z_{cu_j}^{ite\_i}\right) + c_2 r_2 \left(P_{cu_g} - Z_{cu_j}^{ite\_i}\right) \qquad -(22)$$

In Eq. (21) and (22) the $x^{pi}$and x^{pcu}represents the introductory weight factor and r_1 and, r_2 are two random number scattered between (0 and, 1) where, c_1 and c_2 are two scaling factors. The introductory weight factor is calculated by the following equation.

$$x^p = \frac{x_{init}^p - (x_{init}^p - x_{term}^p)^{ite\_i^2}}{ite_{max}^2} \qquad -(23)$$

The x_{init}^p displays the initial weight which is $x_{init}^p = 0$ in the starting phase where the x_{term}^p indicate the terminal weight which is set as slanderers given in [30]. the ite_{max} and

ite_i indicate the maximum iteration count and the present iteration counts sequentially. Subsequently the position of the particles Z_I and, Z_{cu} is calculated by:

$$Z_I^{ite+1} = Z_I^{ite} + v_i^{Pi+1} \qquad -(24)$$

$$Z_{cu}^{ite+1} = Z_{cu}^{ite} + v_j^{Pcu+1} \qquad -(25)$$

After allocation of the sub-channels by Algorithm 1, this considers as an input of power allocation problem in the initial stage. After that, the proposed PSO-enabled power allocation scheme is executed to optimize the transmit power of the CUs and the IoT devices. The progressive procedure of the proposed power allocation scheme is presented in Algorithm 2.

$\boldsymbol{Algorithm\ 2}: PSO-based\ transmit\ Power$

$Alloctement\ for\ CUs\ and\ IoT\ devices$

$Initialization\ T = 1, Population\ size\ p;$

$Fix\ paremeter\ x_{init}^p\ and\ x_{term}^p$

$Fix\ MAX_{iteration}$

$Set\ k \leftarrow 0;$

$Set\ Random\ location\ (Z_{cu}, Z_i) and,$

$velocity\ (V_i^{p_i}, V_i^{cu})of\ the\ particles.$

$\boldsymbol{Begin}$:

$\boldsymbol{for}\ each\ i\ \boldsymbol{do}$:

$\boldsymbol{if}\ (Z_i^k) > TP_{p_i}^k\ \boldsymbol{than}$

$TP_{p_i}^k \leftarrow Z_i^k;$

$\boldsymbol{end\ if}$

$\boldsymbol{if}\ TP_{p_i}^k > TP_{g_i}^k\ \boldsymbol{than}$

$TP_{g_i}^k \leftarrow TP_{p_i}^k$

$\boldsymbol{end\ if}$

$\boldsymbol{Update\ velocity}\ V_i^{p_i+1}, V_i^{cu+1};$

$\boldsymbol{Update\ location}\ \boldsymbol{Z_I^{ite+1}}, \boldsymbol{and}\ \boldsymbol{Z_{cu}^{ite+1}}$

$\boldsymbol{end\ for}$

$\boldsymbol{end}\ (\boldsymbol{Until\ final\ criterion\ met})$

6. Result and Discussion

In this section, we have presented our simulation results and discussions. We have used the MATLAB programming platform to perform the Monte Carlo simulation. A single-cell scheme is considered with 20 number of cellular users and 50 IoT devices in a cell with the assumption of users are deployed uniformly in 500-meter radius. The QoS requirements of the IoT devices are considered as presented in Table -1 and a data packet size is set to 1.5 KB. The proposed scheme is analyzed with two baseline schemes which are random-based and, exhaustive search-based.

Parameters	**Values**
Cell size	500 meters
Transmit power of Cellular	21dBm
Transmit power of IoT	21dBm
Total CUs	10
Total IoT users	25
Frequency in GHz	2.4
Channel Frequency / MHz	1
AWGN in dBm/Hz	-174
Population density in PSO	40
Number of iteration count	100
Local and Global Scaling Factor C1 and, C2	1.4962
QoS of CUs data rate in Mbps	1.5
QoS of IoT data rate in Mbps	1.5

schemes. The studied parameters which we have considered are presented in Table 2.

- Random-based scheme- In this scheme, the FN allocates the random network resource to the IoT devices along with PSO-based power optimization.
- Exhaustive search-based scheme- In this scheme, the FN performs a brute-force search to allocate the network resource allocation along with the PSO-based power optimization.

In Figure 2(a) we have demonstrated the performance of resource block utilization versus the available IoT devices with the above-mentioned methods. In this simulation, we have set the number of CUs to 25 and the maximum number of IoT devices to 50. In this simulation, we can clearly see that the proposed scheme significantly outperforms in terms of utilization of the available resource blocks with compared schemes. In the initial stage up to 20 IoT devices, all the schemes perform almost the same but when the IoT device increased proposed scheme performs better compared with other schemes. The reason behind that is the proposed scheme is more capable to handle interference as compared with other schemes. The random-based scheme and exhaustive search scheme lacks to provide optimal solutions with the higher number of IoT devices because of its nature.

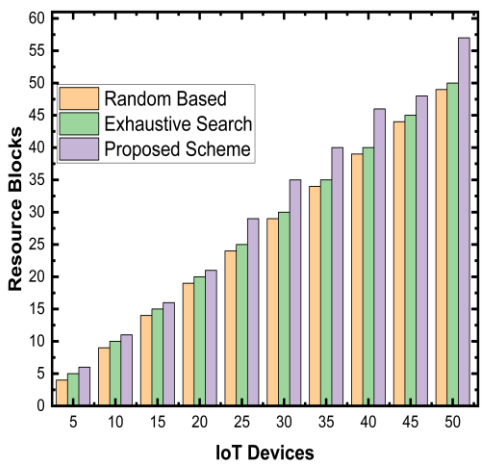

Fig 2(a). Resources block utilization versus IoT devices

Figure 2(b) depicts the performance of overall bandwidth utilization versus the number of IoT devices with other related schemes. The number of CUs is fixed to 25 and every cycle we have increased the 5 IoT devices up to 50. The simulation graph clearly indicates that the proposed scheme efficiently utilizes the limited bandwidth compared with other related schemes. However, in the smaller number of IoT devices, all the schemes perform almost the same but after increasing the IoT devices our scheme outperforms the compared scheme. This happens because of optimally utilization of the QoS function which is able to give a moderate result in terms of overall system sum rate.

Figure 3 depicts the performance of the overall system sum-rate versus the total IoT devices with other related schemes. In this simulation, we can see that the system sum-rate increases with the increased IoT devices however proposed scheme outperforms the compared scheme. This is happened because of the optimal allocation of network resources to the IoT users with the optimized transmit power. The exhaustive search scheme somewhere performs better compared with the proposed scheme but the proposed scheme always fulfills QoS requirements with fast convergence.

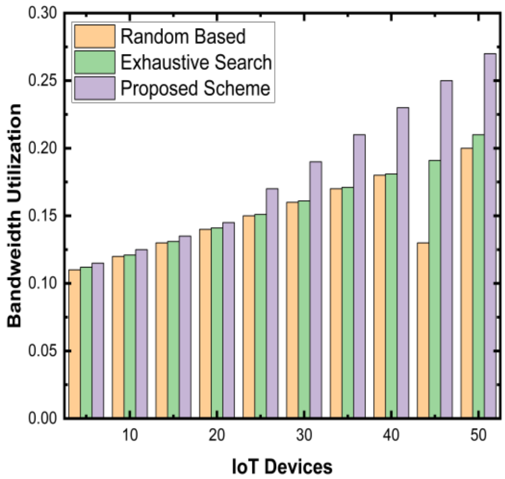

Fig 2(b). Bandwidth utilization versus IoT devices

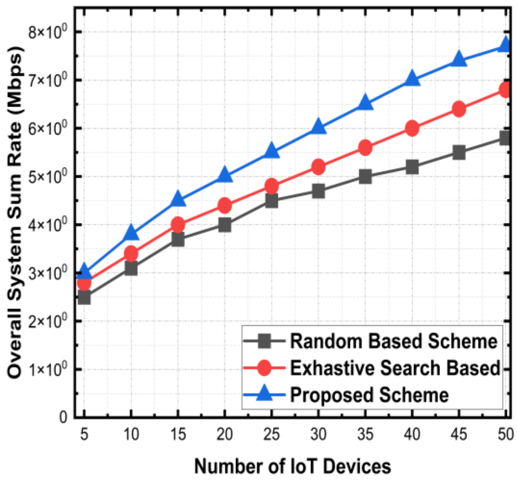

Fig 3. System sum rate vs number of IoT Devices

Figure 4 display the performance of average BER versus the IoT users with the random-based and exhaustive search-based scheme. We can see that the BER rate of all the schemes is identical in the smaller number of IoT devices (i.e. >20) but after IoT devices increase the BER rate of the proposed scheme is maintained to the allowed threshold limit but the other scheme lacks to provides the QoS awaited solutions. The reason behind that is both the random-based and exhaustive search-based schemes degrades the performance if the size of the problem is increasing which is reflected in this simulation. The graph shows that the average BER rate of the proposed scheme is always admirable with the compared scheme.

Figure 5 depicts the achievement of transmit power versus the total data rate with random-based and exhaustive search-based scheme. In this simulation, we have fixed the number of CUs to 20 and the number of IoT to 50 and every cycle we increase the transmit power. The graph shows that increased transmit power also increases the system sum rate. However, our proposed scheme performs better in terms of providing the higher data rate with less transmit power. The increased transmit power also increases the interference; this can degrade the overall system sum-rate but our proposed scheme minimizes this interference efficiently by allocating the network resources away from IDA to maintain the minimum interference.

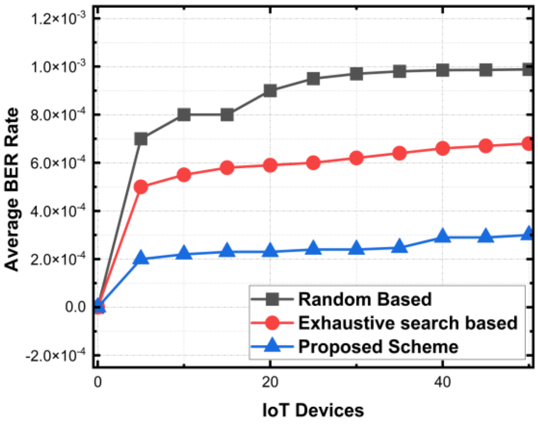

Fig 4. Average BER vs IoT Devices

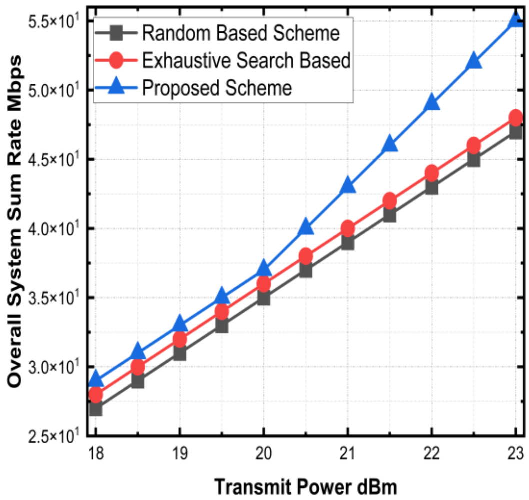

Fig 5. System sum rate vs Transmit power

Figure 6 portrays the convergence graph of the recommended method and the exhaustive search-based scheme. In this simulation, we have fixed the maximum iteration count to 500 rounds and the network resource allocation is done by the proposed IDA-based scheme and exhaustive search-based scheme. After that, the power allocation is applied to both the scheme as Proposed PSO-based schemes. The presented graph clearly indicates that our proposed scheme converges faster compared to the exhaustive search-based scheme. The prominent reason behind that is the network resource allocation of the proposed scheme provides a more robust solution than the exhaustive search-based scheme which will converge fast to the global optimum.

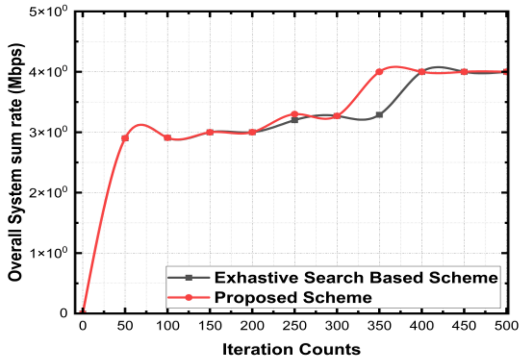

Fig 6. System sum rate vs Transmit power.

Figure 7(a), and (b) portray the evaluation of the transmit power allocation of the CUs and IoT users. In this simulation, the upper bound of the CUs to 20 and the IoT users to 50 where the maximum transmit power is fixed to the 23 dBm. The graph indicates that the proposed power allocation scheme almost every time optimizes power of both the cellular and IoT users which is beneficial to minimize the interference. Here minimum interference will provide benefits in terms of the increased data rate of the users.

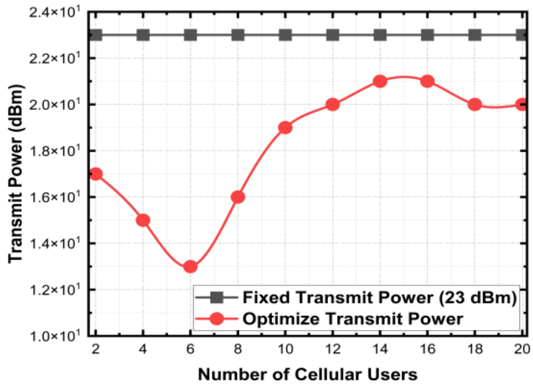

Fig 7a. System sum rate vs Transmit power.

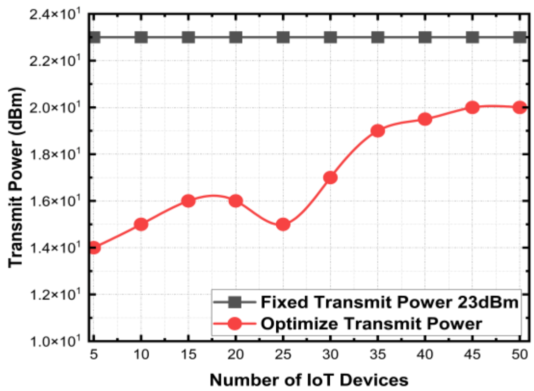

Fig 7b. System sum rate vs Transmit power.

7. Conclusion and Future Work

In this study, we have examined the radio resource allocation scheme for the considered fog based IoT network. Where we have maximized the overall network throughput along with the assurance of permissible BER rate. We have analyzed that the proposed scheme is able the handle the different QoS requirements of the heterogeneous IoT network. In the proposed scheme, we have divided the resource allocation problem into two sub-problems as channel allocation and power optimization. The proposed channel allocation scheme allocates the optimal channels of CUs to reuse the IoT users based on the IDA-based algorithm. The power allotment method optimizes the power of both the CUs and IoT users by the proposed PSO-based algorithm. The simulation result displays that the proposed scheme outperforms other baseline methods in terms of increased data rate, optimize transmit power, and minimum allowable BER rate of different IoT users.

In future, we will consider more QoS parameters like energy efficiency, delay, low latency, etc with the multi-cell model to extend this work.

Author contributions

Author 1: Krati Dubey: Conceptualization, Methodology, Software, Field study Writing-Original draft preparation, Software, Validation. Author 2 Dr Sudhakar Pandey: Reviewing and Editing**,** and Author 3 Dr. Sanjay Kumar: Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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