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Optimal Resource Allocation in Energy Efficient Internet of Things Networks with Imperfect CSI

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***Abstract*—Internet of Things (IoT) is an emerging networking paradigm that enhances smart device communications through internet-enabled systems. Due to massive IoT devices connectivity with economic and greenhouse emission effects, the energy efficiency poses critical concerns. Under imperfect channel state information (CSI), this paper investigates joint optimization of user selection, power allocation and the number of activated Base Station (BS) antennas of multiple IoT devices considering the transmit power and different quality of service (QoS) requirements in combinatorial mode to maximize energy efficiency. The optimization problem formulated is a non-convex mixed-integer nonlinear programming, which is NP-hard with no practical solution. The primal optimization problem is transformed into tractable convex optimization problem and separated into inner and outer loop subproblems. The paper proposed joint energy efficient iterative algorithm, which utilizes successive convex approximation technique and Lagrangian dual decomposition method to achieve near-optimal solutions with guaranteed convergence. Simulation results are provided to evaluate the proposed algorithm and its significant performance gain over the baseline algorithms in terms of energy efficiency maximization.**

***Index Terms*—Energy Efficiency maximization, Lagrangian dual decomposition, Internet of Things, power allocation and user selection**

I. Introduction

The advancement of Internet of Things (IoT) systems is a promising technology where smart devices are interconnected to exchange network information through communication infrastructure to improve daily activities [1]. The communication infrastructure comprises of technologies and other protocols to facilitate cyber-physical objects to effectively exchange data. It is projected that by 2025, more than 50 billion IoT devices will be connected to internet-enabled systems. Due to the increasing growth of IoT devices [2], there is an alarming rate of energy consumption, leading to economic and environmental concerns among both network operators and subscribers. In 2017, researchers observed that there is a dramatic increase of 2% in total carbon dioxide emission, whereby only wireless network users contribute about 0.02% [3] annually.

Adopting large antennas at the base station (BS) has an adverse effects of increasing the energy consumption of IoT networks and selecting antenna optimally is much challenging [4]. The energy consumption of large BS antennas is a growing global concern due to energy scarcity and production cost [5]. Hence, optimizing BS antenna selection is indispensable and can minimized energy consumption while satisfying the quality of service (QoS) in practical design of IoT networks.

Energy efficiency optimization is a promising approach to enhance fully resource utilization and energy saving in the IoT networks as massive IoT devices are connected daily [6]. Designing an energy efficient IoT system under imperfect channel state information (CSI) have attracted attention among the researchers, since in perfect CSI, obtaining a realistic IoT system is computationally complex due to channel estimation errors [7]. However, how to design energy efficient algorithm for future IoT networks to achieve optimal energy efficiency is an emerging research area in recent times.

A. Motivations and Contributions

Motivated by the aforementioned studies, this paper investigates resource allocation and presents a novel optimization model that examines a computationally effective heuristic solution to the problem of energy efficiency maximization. An energy efficient joint design of power allocation, user selection, and number of activated BS antennas under imperfect CSI in IoT systems while guaranteeing QoS requirements is presented. The key contributions are summarized in this paper as follows:

1) This paper examines resource allocation and formulates a non-convex mixed-integer nonlinear programming (MINLP) problem subject to transmit power and different QoS provisioning under imperfect CSI to maximize energy efficiency.
2) A novel energy efficient algorithm with low-computational complexity is proposed to jointly optimize user selection, power allocation and activated BS antennas to obtain practical solutions to enhance the energy efficiency performance.

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3) Extensive simulations are performed and the results reveal the robustness of the proposed algorithm and its superior performance over the baseline algorithms.

B. Structure of Paper

This paper is organized as follows. Section II examines the related works and Section III provides the description of the network system model. Section IV provides energy efficiency optimization to formulate an optimization problems, while Section V discusses the proposed iterative algorithms to achieve optimal solutions. Section VI gives performance evaluations and discussions. Section VII concludes this paper.

II. Related works

Several studies have been done on optimizing physical layer transmissions to reduce the total transmission power while guaranteeing QoS for all mobile user equipment (UEs) in the downlink IoT networks [8, 9]. Khalfi *et al.*, [10] presented a framework for joint optimization of data transfer and energy to minimize the total system energy consumption. Lv *et al.*, [11] designed an optimized energy efficient massive IoT network to simultaneously connected and scheduled IoT devices to achieve optimal number of relay antennas, transmit power and density of massive IoT devices in given network coverage area. An energy efficient resource allocation techniques have been examined for user grouping to maximize energy efficiency in IoT networks [12]. The authors optimized power and time allocation to enhance energy harvesting and information transfer. Ansere *et al.*, [13] investigated a dynamic user selection algorithm to decrease energy consumption for data transmission in IoT systems. Zhai *et al.*, [14] applied a stochastic optimization method by jointly optimizing user scheduling and power allocation (JUSPA) algorithm to maximize energy efficiency in the IoT system. The authors exploited the Lyapunov optimization technique [15] to introduce an operative online algorithm to attain optimal solutions. Salh *et al.*, [16] investigated joint optimization of power allocation and user association to maximize energy efficiency in distributed MIMO systems. They proposed efficient iterative algorithm to achieve optimal power allocation using Netwon's methods and optimal user association by Lagrangian dual decomposition approach. Choi *et al.*, [17] designed an energy efficient model to jointly optimize power allocation, user selection, and precoding under imperfect CSI in multi-user MIMO systems.

Liu *et al.*, [18] proposed energy efficient algorithm with low complexity massive MIMO systems. An optimal number of activated BS antennas was examined for massive MIMO systems [19]. However, both [18] and [19] paid no attention to efficient user selection to optimize power allocation. Shahini *et al.*, [20] designed a framework for energy efficient resource allocation for IoT networks to jointly optimize power allocation and subchannel allocation (JPASA) algorithm subject to transmit power, data rate fairness and interference constraints. However, the authors failed to optimize the number of BS antennas to lessen energy consumption. Much of energy consumption takes place at the BS. Based on power consumption model in [21, 22], the optimal system parameters are known to improve energy efficiency in massive MIMO systems, which is similar to massive IoT systems, for connecting large number of IoT devices. Li *et al.*, [23] explored the joint power allocation and antenna selection in massively distributed antenna systems to maximize the energy efficiency subject to fixed average transmit power. Therefore, designing an energy efficient joint resource allocation algorithm for IoT systems, which can optimize user selection, power allocation and the number of activated BS antennas under imperfect CSI [24] while guaranteeing QoS requirements for all IoT devices is significantly indispensable and needs further research.

Notations: This paper adopted the following notations: bold, italic and uppercase designate column vectors, matrices and random variables, respectively. $\boldsymbol{I}_M$ represents a identity matrix of size $M \times M$ and $\boldsymbol{X}^T$ is the complex conjugate transpose of matrix X. The Euclidean norm and the expectation operator are symbolized by $|.|$ and $\mathbb{E}\{.\}$, respectively. Lastly, $z \sim \mathcal{CN}(0, \sigma^2)$ indicates a complex additive white Gaussian noise with zero mean and variance σ^2.

III. Network System Model

This system model considers a downlink data transmission in IoT networks consisting of BS and UEs as illustrated in Fig.1. The UEs are provided with sensors to enhance data transmission reliability over subchannels. Additionally, UE exploits subchannel opportunistically via BS, where each UE is allowed to connect only to one BS. The BS broadcasts energy signal to the neighbor UE, assuming the UE has perfect CSI between the transmitting BS and UE receiver. Each UE senses available sub-channels independently and stores its energy temporarily to transmit data to the destination. Both the sets of distributed UEs and BSs are represented as $n \in \{1, 2, ..., N\}$ and $m \in \{1, 2, ..., M\}$, respectively. It is assumed that the UEs and BS function on a time-division-duplexing protocol at coherence time. $\mathbf{q}_{m,n} = [q_{m,1,n}, ..., q_{m,n,M}]^T \in \mathbb{C}^{M \times N}$ is assumed to be small-scale fading channel matrix from *m*th BS to *n*th UE. Let $\alpha_{m,n}$ signifies the coefficient of large-scale fading channel. Therefore, the communication channel $h_{m,n}$ between the *n*th UE and *m*th BS can be modeled as

$$\mathbf{h}_{m,n} = \sqrt{\alpha_{m,n}}\hat{\mathbf{q}}_{m,n} \tag{1}$$

The minimum mean-square error (MMSE) estimate [25] $\boldsymbol{q}_n$ of *n*th UE is expressed as

$$\hat{\boldsymbol{q}}_n = \frac{\kappa_n p_n}{\kappa_n p_n + 1} q + \frac{\sqrt{\kappa_n p_n}}{\kappa_n p_n + 1} \boldsymbol{w}_n \tag{2}$$

where $\boldsymbol{q}_n$ is the precoding vector for maximum ratio transmission, κ_n is the number of pilot symbols per coherence interval and where p_n indicates the power transmitted from the *m*th BS to the *n*th UE represents the transmit power. The variables of $\boldsymbol{q}_{m,n}$ are independently and identically distributed with Gaussian noise power.

A. Channel Estimation Model

Each UE in uplink transmits data information in IoT networks to each BS for channel estimation. To enhance coherent detection, it is assume that BSs from different cells simultaneously transmit similar set of data information for channel estimation [26, 27]. The modeled data of N users can be represented by $N \times \nu$ for matrix $\mathbf{\Phi}^H$ through a mutual sequence of orthogonal property $\mathbf{\Phi}^H\mathbf{\Phi} = \nu I_N, (N \leq \nu)$.

By activating all antennas at the BS, the received pilot data information, $\mathbf{Y}_n$ for nth UE is given by

$$\mathbf{Y}_n = \sum_{n=1}^{N} \sqrt{\kappa_n p_n}\mathbf{H}_n^T \Phi + \mathbf{W}_n^T \tag{3}$$

where $\boldsymbol{W}_n$ represents the symmetric complex Gaussian distribution for nth UE with zero mean and unit variance, i.e., $\boldsymbol{w}_n \sim \mathcal{CN}(0, \sigma^2)$.

To effectively estimate the channel gain, the $\tilde{\boldsymbol{y}}_{m,n}$ is assumed to be projected onto Φ_n as

$$\tilde{y}_{m,n}^T \triangleq \mathbf{Y}_m^T \Phi^H = \sum_{n=1}^{N} \sqrt{\kappa_n p_n}\mathbf{h}_{m,n}^T + \tilde{\boldsymbol{W}}_n^T, \tag{4}$$

Therefore, the pilot vector received at nth UE is given by

$$\tilde{\boldsymbol{y}}_{m,n}^T = \kappa_n \sqrt{p_n}\mathbf{h}_{m,n}^T + \tilde{\boldsymbol{w}}_{m,n}^T \tag{5}$$

where $\tilde{y}_{m,n}$ and $\tilde{w}_{m,n}$ represent nth column vectors of $\tilde{Y}_{m,n}$ and $\tilde{W}_{m,n}$, respectively. The nth UE can estimates $\mathbf{h}_{m,n}^T$ from $\tilde{\boldsymbol{y}}_{m,n}$. Applying MMSE technique, the estimated channel $\tilde{\boldsymbol{h}}_{m,n}$ is given as

$$\begin{aligned}\tilde{\boldsymbol{h}}_{m,n} &= \{\mathbf{h}_{m,n}\} \\ &+ \tfrac{\sqrt{\kappa_n p_n}\mathrm{Var}\{\mathbf{h}_{m,n}\}}{\kappa_n p_n \mathrm{Var}\{\mathbf{h}_{m,n}\}+1}\left(\tilde{y}_{m,n} - \sqrt{\kappa_n p_n}\{\mathbf{h}_{m,n}\}\right)\end{aligned} \tag{6}$$

where $\mathrm{Var}\{h_{m,n}\} = \left\{\left|h_{m,n} - \{h_{m,n}\}\right|^2\right\}$. Therefore, the channel estimation error, $\boldsymbol{\epsilon}_{m,n}$ can be represented as $\boldsymbol{\epsilon}_{m,n} = \boldsymbol{h}_{m,n} - \hat{\boldsymbol{h}}_{m,n}$, and has distribution expressed as $\boldsymbol{\epsilon}_{m,n} \sim \mathcal{CN}\left(0, \alpha_{m,n}\boldsymbol{I}_M\right)$

B. Data Transmission Model

For the period of data transmission, each BS communicates message information to the connected UEs in the IoT networks [8]. Assuming that each UE connects at most only to one BS, and representing I_m as the set of UEs aided by the mth BS, the data transmitted from the mth BS is given as

$$\boldsymbol{x}_m = \sum_{n=1}^{I_m} \sqrt{p_{m,n}}\boldsymbol{q}_{m,n} z_{m,n} \tag{7}$$

where $z_{m,n}$ denotes the transmitted symbol. Therefore, the signal received for data transmission from mth BS to nth UE is given as

$$\begin{aligned} y_{m,n} &= \boldsymbol{x}_m \boldsymbol{h}_{m,n}^T + \sum_{i=1, i\neq m}^{M} \boldsymbol{x}_m \boldsymbol{h}_{i,n}^T + \boldsymbol{w}_{m,n} \\ &= \sum_{t=1}^{I_m} \sqrt{p_{m,t}}\boldsymbol{h}_{m,n}^T \boldsymbol{q}_{m,t} z_{m,t} \\ &+ \sum_{i=1, i\neq m}^{M} \sum_{t=1}^{I_m} \sqrt{p_{i,t}}\boldsymbol{h}_{i,n}^T \boldsymbol{q}_{i,t} z_{i,t} + \boldsymbol{w}_{m,n} \end{aligned} \tag{8}$$

It is important to note that from the right-hand side of (8), the first term is considered as the desired signal, and the remaining terms are interference and effective noise respectively.

The achievable data rate [16] of mth BS to nth UE is given by

$$r_{m,n} = \log_2(1 + \gamma_{m,n}) \tag{9}$$

where $\gamma_{m,n}$ represents the signal-to-interference-plus-noise ratio (SINR) [19, 23]. The SINR can be expressed as

$$\gamma_{m,n} = \frac{\sum\limits_{t=1}^{I_m} p_{m,t}\left|\mathbf{h}_{m,n}^T q_{m,t} z_{m,t}\right|^2}{\sum\limits_{i=1, i\neq m}^{M} \sum\limits_{t=1}^{I_m} p_{i,t}\left|\mathbf{h}_{i,n}^T q_{i,t} z_{i,t}\right|^2 + \left|\boldsymbol{w}_{m,n}\right|^2} \tag{10}$$

Thus, the maximum achievable rate [25] of data transmission from mth BS to nth UE can be written as

$$R_n = \sum_{m=1}^{M} x_{m,n}\log_2\left(1 + \frac{\mathcal{L}p_{m,n}\lambda_{m,n}}{\sum\limits_{i=1}^{M}\sum\limits_{t=1}^{N} p_{i,t}\alpha_{i,n} + \sigma_{m,n}^2}\right) \tag{11}$$

where $\lambda_{m,n}$ represents the distribution function in $\boldsymbol{h}_{m,n}$.

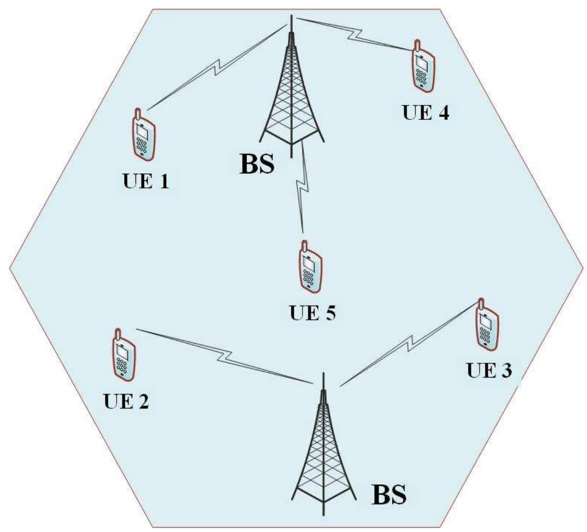

Fig. 1: Illustration of network system model

C. Power Consumption Model

During the data transmission phase from the BS to UEs [23], the total power consumption P_T comprises of circuit power consumption, the transmission power and power amplifiers, and is given as

$$\begin{aligned} P_T &= P_{C_r} + P_t + P_s \sum_{m=1}^{M} \mathcal{K} \\ &= P_{C_r} + \sum_{n=1}^{N}\sum_{m=1}^{M} \frac{1}{\psi} P_{m,n} + P_s \sum_{m=1}^{M} \mathcal{L} \end{aligned} \tag{12}$$

where P_{C_r} represents the circuit power consumption, $P_t = \sum\limits_{n=1}^{N}\sum\limits_{m=1}^{M} \psi P_{m,n}$ is the transmission power, $\mathcal{L}$ signifies the number of the activated BS antennas, P_s is the power consumed for serving an activated BS antenna and ψ is the drain efficiency of power amplifiers respectively.

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D. UE and BS Connection Matrix

In the IoT networks, the UE is connected to the BS using the set of integer binary variables to access the available subchannel for data transmission. Since UE connects to only one BS, the connection variable $x_{m,n}$ between *n*th UE and the *m*th BS is given as

$$x_{m,n} = \begin{cases} 1, \text{if } n \text{ UE connects } to\ m \text{ BS}, \\ 0, \text{otherwise.} \end{cases} \tag{13}$$

IV. Energy Efficiency Maximization

In this section, energy efficiency η is defined as the maximum achievable data rate or system throughput to the total power consumption in IoT network and is measured in bits/sec/Joule [16]. The η can be stated as

$$\eta(\mathcal{U},\mathcal{P},\mathcal{L}) = \frac{R(\mathcal{U},\mathcal{P},\mathcal{L})}{P_T(\mathcal{P},\mathcal{L})} = \frac{\sum\limits_{n=1}^{N} R_n(\mathcal{U},\mathcal{P},\mathcal{L})}{P_T(\mathcal{P},\mathcal{L})}$$

$$\eta = \frac{\sum\limits_{m=1}^{M} x_{m,n}\log_2\left(1+\frac{\mathcal{L}p_{m,n}\lambda_{m,n}}{\sum\limits_{i=1}^{M}\sum\limits_{t=1}^{N} p_{i,t}\alpha_{i,n}+\sigma_{m,n}^2}\right)}{P_{C_r}+\sum\limits_{n=1}^{N}\sum\limits_{m=1}^{M}\frac{1}{\psi}P_{m,n}+P_s\sum\limits_{m=1}^{M}\mathcal{L}} \tag{14}$$

Problem 1 (Energy Efficiency Optimization):

A joint problem is formulated to maximize energy efficiency of UEs taking into accounts of maximum transmit power and different QoS requirements. Mathematically, the η optimization problem is formulated as

$$\begin{aligned} &P1: \max_{(\boldsymbol{\mathcal{U}},\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}})} \eta(\boldsymbol{\mathcal{U}},\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}}) \\ &s.t.: \\ &C1: \sum_{n=1}^{N}\sum_{m=1}^{M} p_{m,n} \le \psi P_{\max}, \forall m \in M, n \in N \\ &C2: \sum_{m=1}^{M} x_{m,n} = 1, \forall m \in M \\ &C3: R_{\min} \le R_m, \forall m \in M, \\ &C4: p_{m,n} \ge 0, \forall m \in M, n \in N, \\ &C5: x_{m,n} \in \{0,1\}, \forall m \in M, n \in N, \\ &C6: 0 \le \mathcal{L} \le \mathcal{L}_{\max}, \mathcal{L} \in N \end{aligned} \tag{15}$$

where $\mathcal{U} \triangleq [x_{m,n}]_{M\times N}$ represents the user selection matrix, $\mathcal{P} \triangleq [p_{m,n}]_{M\times N}$ is the power allocation matrix and $\mathcal{L} \triangleq [p_{m,n}]_{N\times 1}$ is the matrix for activated BS antennas, respectively.

From P1, the respective constraints are defined as follows. C1 entails that the maximum power $P_{\max}$ available should be higher than the total power consumption in the IoT system. C2 and C5 show the importance of joint optimization decision and resource assignments to IoT devices, which guarantees that at most only one UE connects with one BS. C3 limits the minimum data rate $R_{\min}$ required to satisfy the QoS of the UEs, C4 ensures that the allocated power to all UEs is positive and C6 maintains the number of the activated BS antennas.

Remark 1: *Maximizing the energy efficiency in P1 does not imply reducing the total power, but selecting a quality power level and utilize it cautiously.*

Problem 2 (Optimization Problem Transformation):

It is significant to note that the P1 is non-convex optimization and MINLP [28]. Due to its NP-hardness, it is difficult to achieve feasible solution. Let Ψ indicates the feasible domain, the optimization problem becomes tractable, where the C2 and C5 are relaxed continuous. Hence, the P1 is now transformed into subtractive form as

$$\begin{aligned} &P2: \max_{\boldsymbol{\mathcal{U}},\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}}} \{R_{m,n}(\boldsymbol{\mathcal{U}},\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}}) - \eta P_T(\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}})\} \\ &s.t.: C1, C2, C3, C4, C5 \end{aligned} \tag{16}$$

Theorem 1 (*Problem Equivalence*)
If

$$F(\eta) = \max \sum_{n=1}^{N} R_n(\boldsymbol{\mathcal{U}}^*,\boldsymbol{\mathcal{P}}^*,\boldsymbol{\mathcal{L}}^*) - \eta^* P_T(\boldsymbol{\mathcal{P}}^*,\boldsymbol{\mathcal{L}}^*) = 0 \tag{17}$$

then optimal energy efficiency, η^* is given by

$$\eta^* = \frac{\sum\limits_{n=1}^{N} R_n(\boldsymbol{\mathcal{U}}^*,\boldsymbol{\mathcal{P}}^*,\boldsymbol{\mathcal{L}}^*)}{P_T(\boldsymbol{\mathcal{P}}^*,\boldsymbol{\mathcal{L}}^*)} = \max\frac{\sum\limits_{n=1}^{N} R_n(\boldsymbol{\mathcal{U}},\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}})}{P_T(\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}})} \tag{18}$$

Proof: The Theorem 1 can be proved following a similar method as given in [29]. Therefore, the P2 is now be considered as tractable convex optimization and has practical solution.

Moreover, to attain optimal solution in P2, the QoS constraint in C3 must effectively allocates resource to all UEs. Taking the optimal solution of C6 to be the upper bounded and the continuous variables assumed to relax the system based on C5 and C6, then the relaxed optimization is given by

$$\begin{aligned} &\sum_{m=1}^{M} x_{m,n} = 1, x_{m,n} \in [0,1], \forall m \in M, n \in N, \\ &0 \le \mathcal{L} \le \mathcal{L}_{\max}, \forall m \in \mathcal{L}. \end{aligned} \tag{19}$$

V. Proposed Iterative Algorithm for Maximizing Energy Efficiency

In this section, an energy efficient method is proposed to tackle P1, by examining the nonlinear fractional programming to transform the objective function in P1.

A. Successive Convex Approximation

With given $\mathcal{U}$, the corresponding sub-problem in (16) can be solved for both $\mathcal{P}$ and $\mathcal{L}$, respectively. It is observed that (16) is non-concave function and $\mathcal{L}$ has optimization variables. Hence, the $\mathcal{L}$ can be relaxed to achieve an optimal value as $\mathcal{L} = \hat{\mathcal{L}}$. The successive convex approximation (SCA) algorithm [30] can be applied through the relation

$$\log(1+\omega_{m,n}) \ge f(\omega_{m,n}, k_{m,n}, d_{m,n}) = k_{m,n}\omega_{m,n} + d_{m,n} \tag{20}$$

This means that the SCA algorithm for adaptive values of $k_{m,n}$ and $d_{m,n}$ give the tight lower bound for the function $\omega_{m,n}$.

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Assuming $\omega_{m,n} = \tilde{\omega}_{m,n}$, the parameters of the functions in (20) are defined as

$$k_{m,n} = \frac{\tilde{\omega}_{m,n}}{1+\tilde{\omega}_{m,n}}; d_{m,n} = \log\left(1+\tilde{\omega}_{m,n}\right) - \frac{\tilde{\omega}_{m,n}\log\omega_{m,n}}{1+\tilde{\omega}_{m,n}} \tag{21}$$

From equation (9), the approximated lower bound in $r_{m,n} = \log_2(1+\gamma_{m,n})$ is taken as $\gamma_{m,n} = \omega_{m,n}$, and the variables are approximated as $\hat{\mathcal{P}} = \log\mathcal{P}$ and $\hat{\mathcal{L}} = \log\mathcal{L}$, respectively. Hence, the optimization problem is approximated as

$$\begin{aligned}
&P3: \max_{\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{L}}} \sum_{n=1}^{N} \hat{R}_n(\hat{\boldsymbol{\mathcal{P}}}, \hat{\boldsymbol{\mathcal{L}}}, \boldsymbol{k}, \boldsymbol{d}) - \eta P_T(\boldsymbol{\mathcal{P}}, \boldsymbol{\mathcal{L}})\\
&s.t.:\\
&C1: R_{\min} \le \hat{R}_m, \forall m \in M,\\
&C2: \sum_{n=1}^{N} e^{\hat{\mathcal{P}}_{m,n}} \le \psi P_{\max}, \forall m \in M, n \in N,\\
&C4: \hat{\mathcal{L}} \le \log\mathcal{L}_{\max}, \mathcal{L} \in N
\end{aligned} \tag{22}$$

The objective function in (22) becomes concave and hence is convex optimization problem.

B. Dual Decomposition Problem

In this subsection, the Lagrangian dual decomposition method [31] is applied to the transformed optimization problem. Lagrange multipliers ($\boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\mu}$), associated with BS power constraint and antenna usage constraints are introduced into P3. The formulated problem based on Lagrangian function from the primal optimization problem P1 becomes

$$\begin{aligned}
&L(\hat{\boldsymbol{\mathcal{P}}}, \hat{\boldsymbol{\mathcal{L}}}, \boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\mu})\\
&= \sum_{m=1}^{M}\sum_{n=1}^{N} \left[k_{m,n}x_{m,n}\log_2(\bar{\gamma}_{m,n}) + k_{m,n}x_{m,n}\right]\\
&-\eta\left[P_{C_r} + \sum_{n=1}^{N}\sum_{m=1}^{M}\frac{1}{\psi}P_{m,n} + P_s\sum_{m=1}^{M}\hat{L}\right]\\
&+\sum_{n=1}^{N}\rho_n\left[\sum_{n=1}^{N}\left[k_{m,n}x_{m,n}\log_2(\bar{\gamma}_{m,n}) + d_{m,n}x_{m,n}\right] - R_{\min}\right]\\
&+\sum_{m=1}^{M}\beta_k\left(P_{\max} - \sum_{n=1}^{N}e^{\hat{\mathcal{P}}_{m,n}}\right) + \sum_{m=1}^{M}\mu_m\left(\mathcal{L}_{\max} - \sum_{n=1}^{N}e^{\hat{\mathcal{L}}}\right)
\end{aligned} \tag{23}$$

where $\boldsymbol{\rho} = [\rho_0, \rho_1, ...\rho_N]^T, \boldsymbol{\beta} = [\beta_0, \beta_1, ...\beta_M]^T$ and $\boldsymbol{\mu} = [\mu_0, \mu_1, ...\mu_M]^T$, respectively

Therefore, the dual optimization problem is given by

$$\min_{(\boldsymbol{\rho},\boldsymbol{\beta},\boldsymbol{\mu})>0} \max_{\hat{\boldsymbol{\mathcal{P}}},\hat{\boldsymbol{\mathcal{L}}}} L(\hat{\boldsymbol{\mathcal{P}}}, \hat{\boldsymbol{\mathcal{L}}}, \boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\mu}) \tag{24}$$

C. Upper Bound Algorithm

The dual decomposition is decoupled iteratively into inner loop aims to maximize both power allocation and number of activated BS antennas over Lagrange multipliers and outer loop, also known as a master dual problem to minimize Lagrange multipliers, which enhances the optimal user selection algorithm in IoT networks.

1) Inner Loop:

In this section, the transmit power $\mathcal{P}$ and the number of activated BS antennae $\mathcal{L}$ are jointly optimized when the user selection $\mathcal{U}$ is given.

Theorem 2: *Assuming $\bar{\mathcal{P}}$ and $\bar{\mathcal{L}}$ guarantee the KKT conditions [31], the inner loop maximization obtained for the Lagrangian function are given as*

$$p_{m,n} = \frac{(\rho_n+1)k_{m,n}d_{m,n}}{\sum_{m=1}^{M}\sum_{n=1}^{N}\frac{(1+\rho_n)k_{m,n}d_{m,n}\alpha_{m,n}}{\sum_{i=1}^{M}\sum_{t=1}^{N}p_{i,t}\alpha_{i,n}+\sigma^2_{m,n}} + \left(\mu_m + \frac{\eta}{\psi}\right)\ln 2} \tag{25}$$

and

$$\mathcal{L} = \frac{\sum_{n=1}^{N}(\rho_n+1)k_{m,n}d_{m,n}}{\left(\frac{\eta p_s}{\psi_m}+1\right)\ln 2}. \tag{26}$$

Proof: Please refer to Appendix A ■

Theorem 2 confirms that both $p^*_{m,n}$ and $\mathcal{L}^*$ can achieve optimal energy efficiency with guaranteed convergence.

2) Outer Loop:

The outer loop enhances the optimal user selection algorithm to minimize Lagrange multipliers. The user selection $\mathcal{U}$ is optimized when both $\mathcal{P}$ and $\mathcal{L}$ are given. Hence, the following optimization problem is formulated for $\mathcal{U}$ as

$$\begin{aligned}
&P4: \max_{\mathcal{U}} \sum_{n=1}^{N} R_n\\
&s.t.:\\
&x_{m,n} \in [0,1], \forall m \in M, n \in N\\
&\sum_{m=1}^{M} x_{m,n} = 1, \forall n \in N
\end{aligned} \tag{27}$$

Optimizing user selection fully utilizes the resource allocation to maximize energy efficiency while maintaining QoS requirements for all UEs in the IoT networks. The user selection variable $x_{m,n}$ is defined to enhance the updating algorithm and is given by

$$x^{\tau+1}_{m,n} = \begin{cases} 1, & m = m^{\tau}_n\\ 0, & \text{otherwise.}\end{cases} \tag{28}$$

where

$$\begin{aligned}
m^{\tau}_n &= \underset{m\in M}{\operatorname{argmax}}\ \{R_n\}\\
&= \underset{m\in M}{\operatorname{argmax}}\left\{x_{m,n}\log_2\left(1+\frac{\mathcal{L}p_{m,n}\lambda_{m,n}}{\sum_{i=1}^{M}\sum_{t=1}^{N}p_{i,t}\alpha_{i,n}+\sigma^2_{m,n}}\right)\right\}
\end{aligned} \tag{29}$$

The sub-gradient method with constant step size is employed to tackle the master problem minimization in (29). Selection of constant step size is largely inspired by its practical significance to achieve primal solutions and also improve the convergence rate analysis [28, 31]. Thus, the proposed algorithm is updated by

$$\begin{aligned}
\rho_n(\tau+1) = \Big[\rho_n(\tau) - \varsigma(\tau)\Big\{\sum_{n=1}^{N}(k_{m,n}R_n\\
+ x_{m,n}d_{m,n}) - R_{\min}\Big]^+
\end{aligned} \tag{30}$$

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$$\beta_n(\tau+1) = \left[\beta_n(\tau) - \phi(\tau)\left\{\psi P_{\max} - \sum_{n=1}^{N} 2^{\bar{p}_{m,n}}\right\}\right]^+ \tag{31}$$

$$\mu_n(\tau+1) = \left[\mu_n(\tau) - \varphi(\tau)\left\{\mathcal{L}_{\max} - 2^{\bar{\mathcal{L}}}\right\}\right]^+ \tag{32}$$

where τ represents the maximum iteration number. However, the step sizes of iterations ς, ϕ,and φ are cautiously selected to enhance the square summation of step sizes in order to ensure guaranteed convergence.

D. Proposed Algorithm

This section investigates a proposed resource allocation algorithm to jointly optimize power allocation, user selection, and number of activated BS antennas (JPAUS) to maximize energy efficiency in IoT systems. Particularly, for value of η given, the proposed JPAUS algorithm optimizes the power and resource allocations as implemented practically in Algorithm 1. Since Algorithm 1 is uses the concept of Dinklebach method [29], the η value can be updated in steps (4 - 14) based on the solutions achieved from step (3 - 8). The extensive simulations are performed with guaranteed convergence of Algorithm 1.

Algorithm 1: Proposed Joint Power Allocation, User Selection, and Activated BS Antennas Algorithm.

Input: Set $\theta \leftarrow$ maximum tolerance and $\tau_{\max} \leftarrow$ maximum iteration index;

1 Initialize $\rho, \lambda, \mu \geq 0$
2 Initialize $\boldsymbol{p}(0)$, compute $\{R_n\}$ for all $n, t = 0$
3 **for** $0 \leq \tau \leq \tau_{\max}$ **do**
4   **while** $\theta > t$ **do**
5   **if** $R_{n,k}\left(\mathcal{U}^*, \mathcal{P}^*, \mathcal{L}^*\right) - \eta P_T\left(\mathcal{U}, \mathcal{P}, \mathcal{L}\right) < \theta$ **then**
6   Compute $\mathcal{P}^*$, $\mathcal{L}^*$ and $\mathcal{U}^*$ according to (26), (28), and (31)
7   Update $\rho_n(\tau+1)$, $\beta_n(\tau+1)$ and $\mu_n(\tau+1)$ using (32) - (34) to guarantee convergence.
8   Compute $m_n^{\tau} = \underset{m \in M}{\operatorname{argmax}} \{R_n\}$
9   Set $\mathcal{U}^* \leftarrow \mathcal{U}, \mathcal{P}^* \leftarrow \mathcal{P}, \mathcal{L}^* \leftarrow \mathcal{L}$, and $\eta^* \leftarrow \eta$
10   **else**
11   Compute $\eta^* = \frac{R_{n,k}(\mathcal{U}^*, \mathcal{P}^*, \mathcal{L}^*)}{P_T(\mathcal{U}^*, \mathcal{P}^*, \mathcal{L}^*)}$
12   **if** $\tau == \tau_{\max}$ **then**
13   Exit
14 $\tau = \tau + 1$
15 Return η^*, $(\mathcal{U}^*, \mathcal{P}^*, \mathcal{L}^*)$

E. Computational Complexity Analysis

This section analyses the computational complexity between the proposed JPAUS algorithm and the baseline algorithms, i.e., JPASA and JUSPA algorithms. In the JPASA algorithm [20], the resources are allocated to the subchannel to each loop while the JUSPA algorithm [14] can only achieve optimal solution at high transmit power.

However, both JPASA and JUSPA algorithms have complexities of $O\left(M^N\right)$ and $O\left(NM^2\right)$, respectively. The total complexity of the proposed JPAUS algorithm is $O\left(M(N+1)^3\right)$, which has a polynomial complexity to enable its practical implementation. For large-scale IoT networks, where *M* and *N* are large, the proposed JPAUS algorithm is suitable, which can efficiently minimize the computation complexity while satisfying the system performance.

VI. Performance Evaluations and Discussions

This section evaluates the proposed joint energy efficient algorithm performance and compared with baseline algorithms through extensive computational simulations to maximize energy efficiency in IoT systems.

A. Simulation Parameters

The following parameters are used in the simulations. The designed cell is made up of two (2) BS equipped with $\mathcal{L}_{\max} = 200$ antennas at a circular radius of 1 Km. The modeled path-loss is expressed as $128.1 + 37.5 * \log_{10}(l)$, where l indicates the distance between the source and destination devices in meters. The modeled network functioned in large-scale Rayleigh fading channel with random variables, independently and identically distributed with unit variances [32]. 30 users (UEs) are uniformly distributed in each cell, where the transmission bandwidth, total transmit power and total noise power are set at 18 KHz, 42 dBm and -104 dBm, respectively. In addition, the power consumption for each activated BS antenna is set to be 10 W, power amplifier efficiency is 0.27 and circuit power needed to run elements at each activated BS antenna is 0.2 W [10, 24].

B. Baseline Algorithms

The proposed JPAUS algorithm and the baseline algorithms performance are compared taking into account the channel uncertainties. The selected baseline algorithms are JUSPA algorithm [14], which uses stochastic optimization method through Lyapunov optimization technique to jointly optimize user scheduling and JPASA algorithm [20] that jointly optimizes power allocation and subchannel allocation for energy efficient resource allocation in IoT networks. However, both baseline algorithms ignored to optimize the number of activated BS antennas to minimize energy consumption. All the algorithms were simulated in the same environment and simulation results were averaged over 40 experiments at varying positions of UEs.

C. Simulation Results

1) The impact of the maximum allowed transmit power: Fig. 2 shows energy efficiency plotted against maximum transmit power, $P_{\max}$. The energy efficiency performance is examined in terms of transmit power of the proposed JPAUS with JPASA and JUSPA algorithms to show the superiority of the proposed algorithm. In this simulation scenario, where 10 iterations and 25 UEs are set at minimum data rate requirements, $R_{\min} = 1$ bps/Hz, respectively. As the transmit

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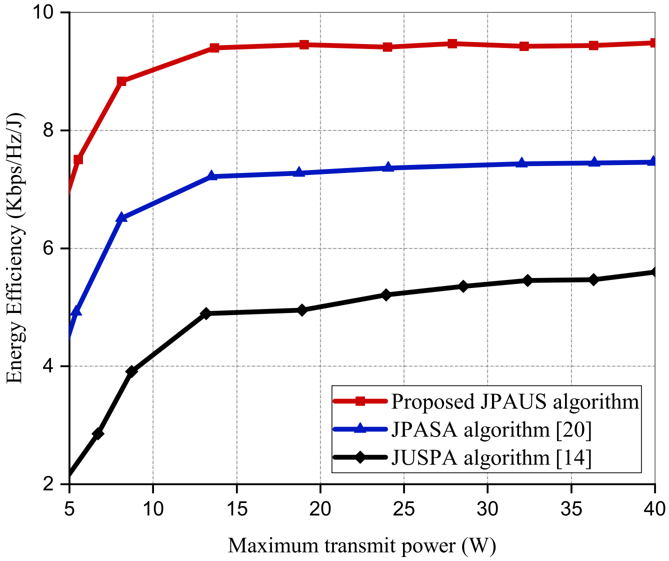

Fig. 2: Energy efficiency versus maximum transmit power

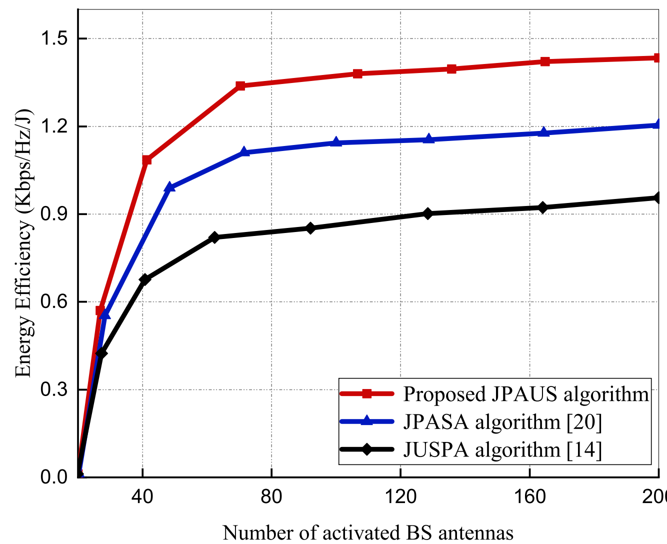

Fig. 3: Energy efficiency versus the activated BS antennas

power increases, it can be observed that the energy efficiency increases.

At $P_{\max} < 15$ W regime, the energy efficiency performance for all algorithms increases linearly as $P_{\max}$ enlarges. When $P_{\max} \geq 20$ W, the energy efficiency is stable as the total power consumption and spectral utilization efficiency performance increases steadily. All the algorithms yield practically the same performance gain.

It is observed that when the number of UEs increases at the $P_{\max}$ regime, the JUSPA algorithm consumes more power at the BS and therefore, fails to satisfy the QoS requirements for all users. In addition, the JPASA algorithm improves the energy efficiency performance at increasing the minimum data rate in order to maintain the transmission rate of the UEs. At large number of UEs, the proposed JPAUS achieves high performance gain in energy efficiency as compared with the baseline algorithms. It can attain about 95% in energy efficiency gain and fully utilizes the resources to avoid inter-UEs interference. On the contrary, JPASA algorithm outperforms JUSPA algorithm, since the JUSPA algorithm partially utilizes the available resource and hence consumes more energy.

2) Impact of activated BS antennas on energy efficiency: Fig. 3 illustrates the energy efficiency versus the number of activated BS antennas in each cell, for maximum of 200 BS antennas, 15 iterations, 30 UEs, and $R_{\min}$ = 2 bps/Hz, respectively. It can be observed that as the number of UES and the activated BS antenna increase, the energy efficiency increases. Remarkably, at low $P_{\max}$ regime, the proposed algorithm and the baseline algorithms achieved similar system performance for resource allocation to UEs. This is because the multi-cell interference and noise power influence are negligible, which have no effect on the system performance at the low transmit powers.

It is noted that JPASA algorithm optimizes the subchannel for fixed number of UEs while JUSPA algorithm optimizes user selection, respectively. Since the baseline algorithms ignored to optimize number of BS antennas, they activate more BS antennas at low $R_{\min}$ and high $P_{\max}$ regime to achieve optimal energy efficiency. However, the proposed JPAUS algorithm optimizes the number of antennas at the BS to improve energy efficiency performance. It activates few BS antennas as the $P_{\max}$ increases and fully utilizes resource to avoid inter-UEs interference. This can significantly enhanced the system performance to obtain optimal energy efficiency as compared with both baseline algorithms. It worth mentioning that the JUSPA algorithm activates extra BS antennas than JPASA algorithm to satisfy the minimum rate requirements. Consequently, the JUSPA algorithm has a higher energy consumption as compared to other algorithms.

3) The effect of UEs on energy efficiency:

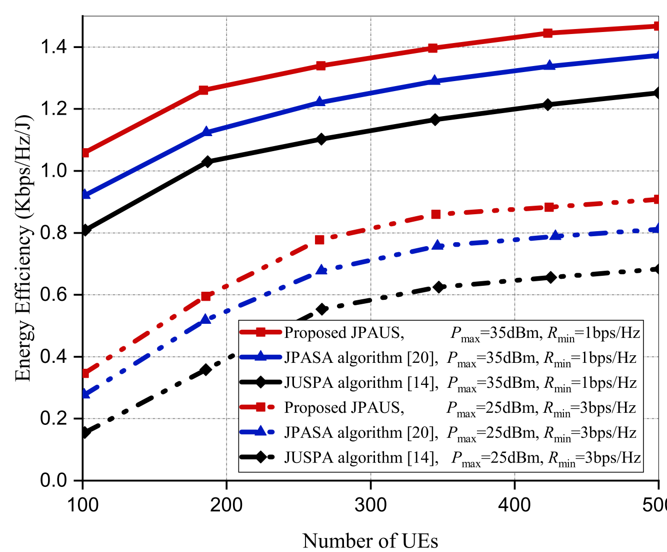

Fig. 4: Energy efficiency versus the number of users at varying maximum transmit power

Fig. 4 shows the energy efficiency compared with the number of UEs with varying $P_{\max}$ and $R_{\min}$, respectively. All the algorithms are jointly simulated and the energy efficiency performance are compared.

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In Fig. 4, it can seen that at high $P_{\max}$ and low $R_{\min}$, the energy efficiency increases as the number of UE grows. The proposed JPAUS algorithm attains better energy efficiency maximization and outperforms the baseline algorithms, due to its high degree of freedom to select the best available BS antenna for data transmission to UEs. It saves more energy by exploiting multi-user diversity technique, which is profitable for the performance of system energy efficiency.

At high QoS requirement, i.e., $R_{\min} = 3$ bps/Hz, more energy and activated BS antennas are required to maintain QoS requirement, leading to decline in energy efficiency performance. The performance gap minimizes due increase in interference among UEs and hence, there is an increase in the energy consumption of the IoT networks. In addition, performance gain deteriorates and the curves become practically identical. On the contrary, the JUSPA algorithm performs least and has lower energy efficiency as compared with JPASA algorithm. JUSPA algorithm needs large amount of circuit power to operate the activated BS antennas and encounters strong interference as the number of UE increases.

4) Comparing the Energy Efficiency Performance under different constraints:

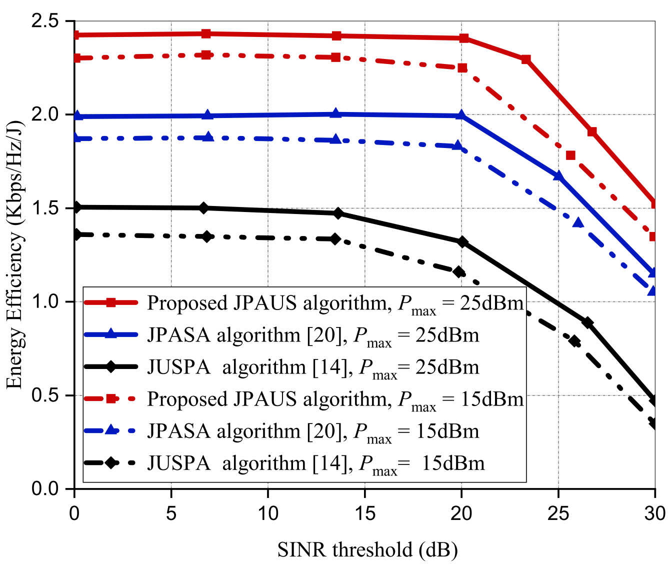

Fig. 5: energy efficiency performance with different SINR thresholds

Fig. 5 demonstrates the energy efficiency performance with varying SINR, γ thresholds. The proposed JPAUS algorithm performance is compared with JPASA and JUSPA algorithms at different $P_{\max}$. When the increasing of γ threshold is not sufficiently large, the proposed JPAUS algorithm can fully utilize resource allocation. This enhances its capability to mitigate inter-UEs interference in achieving better energy efficiency as compared to the baseline algorithms.

Conversely, at $\gamma > 10$ dB regime, the energy efficiency performance worsens for both JPASA and JUSPA algorithms, caused by the declining of the feasible region. However, the JUSPA algorithm has most reduced energy efficiency performance due to increase in γ threshold. Since $P_{\max}$ influences the energy efficiency performances, it is expected that the $P_{\max} = 25$ dB would outperform that of $P_{\max} = 15$ dB.

5) Impact of Activated BS Antennas on maximum transmit power:

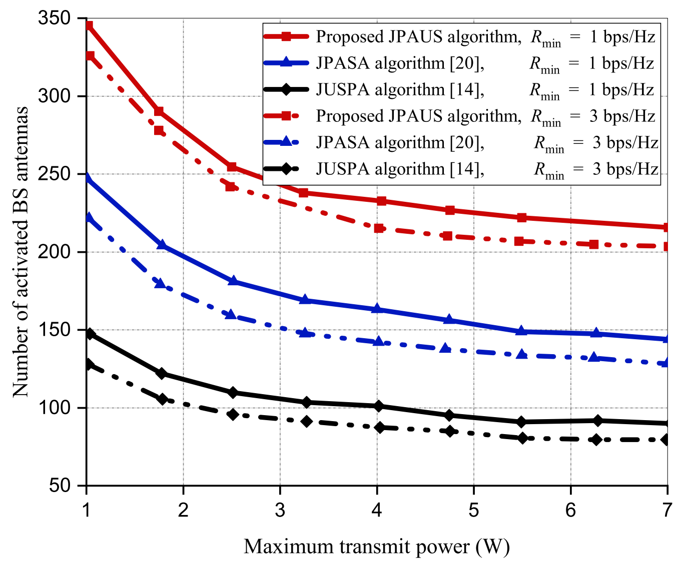

Fig. 6: Number of activated BS antennas versus maximum transmit power

Fig. 6 examines the number of activated BS antennas versus $P_{\max}$ with different $R_{\min}$ taking into account. The simulation parameters are set for maximum of 200 BS antennas, 15 iterations, 30 UEs, and $R_{\min}$ = 2 bps/Hz, respectively. At $P_{\max} < 3$ W regime, and large $R_{\min}$ constraint, the BS activates extra antennas to satisfy the QoS requirements. Because the performance of energy efficiency maximization relied on the large-scale fading, the optimal number of activated BS antennas remain unaltered. A relative stability is achieved as the antennas are not switch on and off frequently to enhance the practical implementation in IoT systems.

At $P_{\max} > 4$ W regime, more number of BS antennas are activated and more radio resource utilized to improve energy efficiency performance. It is obvious in Fig. 6 that as $R_{\min}$ increases, more activated BS antennas are needed to satisfy minimum rate requirements. This means that at large $P_{\max}$ and small $R_{\min}$ regime, few number of BS antennas are optimally activated to achieve maximum energy efficiency. Hence, the proposed JPAUS algorithm activates few BS antennas in attaining higher energy efficiency to significantly improve the system performance in combating inter-UEs interference as compared with baseline algorithms.

6) Impact of transmit power on energy consumption:

Fig. 7 shows the average total power consumption versus $P_{\max}$ in evaluating all the algorithm performance for 30 UEs at 10 iterations. As the UEs increase, all the algorithms monotonically increase and the average total power consumption increases correspondingly. At $P_{\max} \leq 35$ dBm regime, it is evident that the proposed JUSPA algorithm consumes more power as compared to the JPASA algorithm with $L \leq 35$, since more BS antenna activations are required to satisfy the minimum data rate requirement. However, in the $P_{\max} \geq 40$ dBm regime, the increase in all the algorithms become con-

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stant.

In Fig. 7, it is observed that the baseline algorithms, i.e., the JSPA algorithm at L = 65 and JUSPA algorithm at L = 55 have higher average total power consumption as the number of activated BS antennas increase in high transmit power regime in comparison to the proposed JPAUS algorithm. As $P_{\max}$ increases, the proposed JUSPA algorithm gradually attains a constant power consumption and activates only sufficient BS antennas and fully utilizes the available resources to benefit the energy efficiency of the system. On the other hand, the proposed JPAUS algorithm consumes more power than at $L = L_{\max}$, since it activates few number of BS antennas than the proposed algorithm to marginally mitigate inter-UEs interference at low $P_{\max}$ regime.

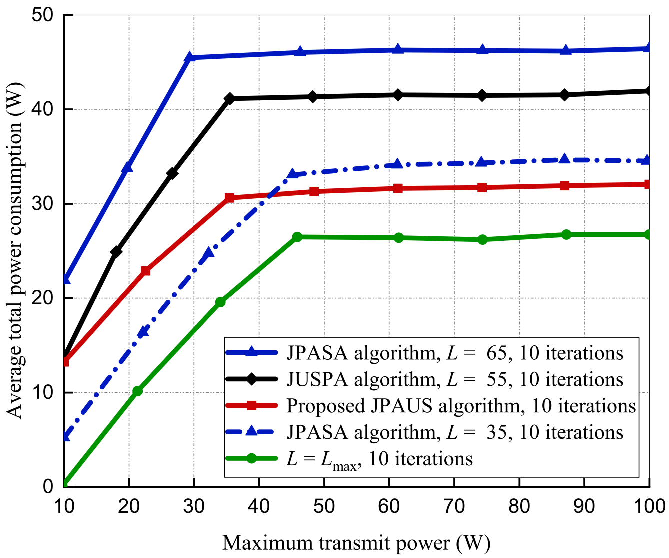

Fig. 7: shows average total power consumption versus maximum transmit power

7) Impact of number of iterations on energy efficiency performance:

Fig. 8 shows the performance of energy efficiency performance versus the number of iterations with different interference threshold. The simulation parameters are set at 15 iterations and uniformly distributed 30 UEs, respectively. All the algorithms converge at three iterations and reach a saturation point before increase linearly. It is expected that the energy efficiency becomes constant as the number of iterations increases.

At $R_{\min} = 3$ bps/Hz regime, extra BS antennas are utilized to maintain the minimum rate requirements for all UEs in IoT systems and consequently, more energy is consumed. At $R_{\min}$ = 1 bps/Hz regime, few number of BS antennas are activated and the performance of energy efficiency is improved. It is observed in Fig. 8 that the proposed JPAUS algorithm achieves optimal energy efficiency and outperforms both JPASA and JUSPA algorithms.

Summary of evaluation results

By the evaluations performed, we demonstrated that the proposed algorithm and the baseline algorithms jointly simulated taking into account power allocation, user selection and activated BS antennas subject to the maximum transmit power and different QoS constraints.

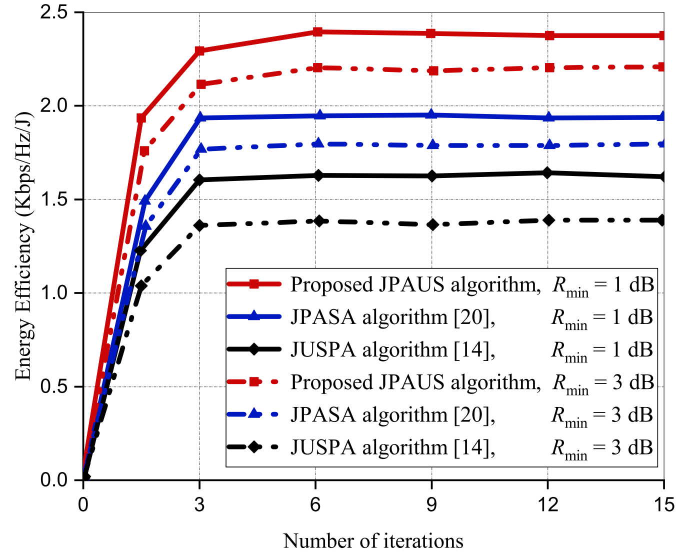

Fig. 8: Performance of energy efficiency versus number of iterations

Under imperfect CSI, the proposed algorithm achieves significant performance gains in energy efficiency maximization over the baseline algorithms. At high $P_{\max}$ and low $R_{\min}$ regime, the number of UEs increases and the proposed algorithm optimally activates few BS antennas to achieve maximum energy efficiency with guaranteed convergence. It fully utilizes resource allocation to mitigate multi-users interference as compared with the baseline algorithms. Therefore, the effectiveness of the proposed algorithm is verified and it efficiently minimizes the number of activated BS antennas to enhance energy efficiency performance while guaranteeing QoS requirements.

VII. Conclusion

This paper examined optimal resource allocation in energy efficient Internet of Things (IoT) networks under channel uncertainties. An optimization problem was formulated to jointly optimize power allocation, number of activated BS antenna, and user selection algorithm to maximize energy efficiency in IoT systems. The paper proposed joint energy efficient iterative algorithm, which utilizes SCA technique and Lagrangian dual decomposition method to achieve optimal solutions with guaranteed convergence and low-computational complexity. Simulations results demonstrated the robustness of the proposed algorithm with a significant gain in energy efficiency performance and its superiority over the baseline algorithms. In addition, the proposed algorithm substantially activates number of BS antennas to improve energy efficiency while guaranteeing QoS provisioning for all UEs in the IoT systems. In the future, considering the spectrum and energy efficiencies tradeoff in IoT systems, as two conflicting system design metrics under imperfect CSI will be explored.

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APPENDIX A

Proof of Theorem 2

By first differentiate $L(\hat{\boldsymbol{\mathcal{P}}}, \hat{\boldsymbol{\mathcal{L}}}, \boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\mu})$ with respect to $p^*_{m,n}$ based on KKT condition is obtained as

$$\begin{aligned}
&\frac{\partial L(\widehat{\mathbf{P}},\widehat{\mathbf{L}},\rho,\beta,\mu)}{\partial \tilde{p}_{m,n}} = k_{m,n}d_{m,n} - \eta 2^{\tilde{p}_{m,n}}\ln 2 \\
&-2^{\tilde{p}_{m,n}} \sum_{m=1}^{M}\sum_{n=1}^{N} \frac{k_{m,n}d_{m,n}\alpha_{m,n}}{\sum\limits_{i=1}^{N}\sum\limits_{t=1}^{M} 2^{\tilde{p}_{i,t}}\alpha_{i,n}+\sigma^2_{m,n}} \\
&-2^{\tilde{p}_{m,n}} \sum_{m=1}^{M}\sum_{n=1}^{N} \frac{\rho_m k_{m,k}d_{m,k}\alpha_{m,k}}{\sum\limits_{i=1}^{N}\sum\limits_{t=1}^{M} 2^{\tilde{p}_{i,t}}\alpha_{i,n}+\sigma^2_{m,n}} \\
&+\rho_n k_{m,n}d_{m,n} - \mu_m 2^{\tilde{p}_{m,n}}\ln 2 = 0
\end{aligned} \tag{33}$$

From (33), $\bar{\mathcal{P}}$ is reverted to the original form $\mathcal{P}$ to determine the corresponding solution through *KKT* conditions. Rearranging terms in (33) as

$$\begin{aligned}
&-p_{m,n} \sum_{m=1}^{M}\sum_{n=1}^{N} \frac{k_{m,n}d_{m,n}\alpha_{m,n}}{\sum\limits_{n=1}^{N}\sum\limits_{t=1}^{M} p_{i,t}\alpha_{m,n}+\sigma^2_{m,n}} \\
&-p_{m,n} \sum_{m=1}^{M}\sum_{n=1}^{N} \frac{\rho_m k_{m,n}d_{m,n}\alpha_{m,n}}{\sum\limits_{n=1}^{N}\sum\limits_{t=1}^{M} p_{i,t}\alpha_{m,n}+\sigma^2_{m,n}} \\
&-\mu_m p_{m,n}\ln 2 - \eta p_{m,n}\ln 2 \\
&= \rho_n k_{m,n}d_{m,n} + k_{m,n}d_{m,n}
\end{aligned} \tag{34}$$

Therefore, the optimal power allocation, $p^*_{m,n}$ for *n*th UE on *m*th subchannel is given as

$$p^*_{m,n} = \frac{(1+\rho_n)k_{m,n}d_{m,n}}{\sum\limits_{m=1}^{M}\sum\limits_{n=1}^{N} \frac{(1+\rho_m)k_{m,n}d_{m,n}\alpha_{m,n}}{\sum\limits_{i=1}^{M}\sum\limits_{t=1}^{N} p_{i,t}\alpha_{m,n}+\sigma^2_{m,n}} + \left(\mu_m + \frac{\eta}{\psi}\right)\ln 2} \tag{35}$$

Similarly, differentiating $L(\hat{\boldsymbol{\mathcal{P}}}, \hat{\boldsymbol{\mathcal{L}}}, \boldsymbol{\rho}, \boldsymbol{\beta}, \boldsymbol{\mu})$ with respect to $\mathcal{L}^*$ based on KKT condition as

$$\begin{aligned}
&\frac{\partial L(\widehat{\mathbf{P}},\widehat{\mathbf{L}},\rho,\beta,\mu)}{\partial \tilde{L}_{m,n}} = \sum_{m=1}^{M}(1+\rho_{m,n})k_{m,n}d_{m,n} \\
&-(\eta p_s + \psi_m)L\ln 2 = 0
\end{aligned} \tag{36}$$

Hence, the optimal number of BS antennas allocation, $\mathcal{L}^*$ for *n*th UE on *m*th subchannel is expressed as

$$\mathcal{L}^* = \frac{\sum\limits_{n=1}^{N}(\rho_n+1)k_{m,n}d_{m,n}}{\left(\frac{\eta p_s}{\psi_m}+1\right)\ln 2} \tag{37}$$

Thus, Theorem 2 is proved to confirm that the optimal power allocation and the optimal number of the activated BS antennas can improved the inner maximization problem.

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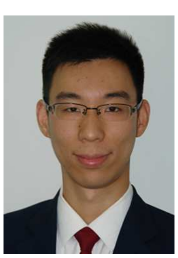

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