# Green-Oriented Dynamic Resource-on-Demand Strategy for Multi-RAT Wireless Networks Powered by Heterogeneous Energy Sources

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***Abstract*— Energy harvesting with combination of multiple cooperating radio access technologies (multi-RAT) is regarded as a promising network paradigm to improve the energy efficiency of 5G networks. In this paper, we propose a resource-on-demand energy scheduling strategy for multi-RAT wireless networks, where the varying energy demand of the network can be satisfied by both grid power and harvested energy. Due to the high sensitivity to uncertainties of energy harvesting, a dynamic network energy queue model is designed first considering the inherently stochastic and intermittent nature of the harvested energy. Then, to minimize time-averaged grid power consumption and make effective utilization of harvested energy, the energy scheduling is formulated as a stochastic optimization problem subject to data queue stability and harvested energy availability, considering the high ynamics of wireless channel states and renewable energy sources. Following the Lyapunov optimization framework, the stochastic grid power minimization problem is decomposed into a network flow control subproblem, a network energy management subproblem, and a network resource allocation subproblem, respectively. In order to solve these subproblems, we develop a dynamic adaptive resource-on-demand (DAROD) algorithm to effectively reduce the grid power consumption cost by allocating the resource efficiently based on the dynamic demands of multi-RAT networks. Finally, the tradeoff between grid power consumption cost and network delay is achieved, in which the increase of network delay is approximately linear with the network control parameter $V$ and the decrease of grid power consumption cost is at the speed of $1/V$. Extensive simulations are conducted to verify the theoretical analysis and show the effectiveness of our proposed algorithm.**

***Index Terms*— Resource-on-demand, multi-RAT networks, resource optimization, energy harvesting.**

## I. Introduction

THE exponential growth of wireless data driven by mobile Internet and smart devices (e.g., smart phones, drones, smart cars and sensors) has triggered the investigation on 5G cellular networks [1], [2]. In order to serve such high data traffic with a massive number of terminals, future 5G networks should be sustainable to support high network capacity with enhanced energy efficiency, since using an extremely large amount of energy to increase the communication capacity will result in unacceptable operating costs for both the network operators and the electricity grid [3]. Hence, reducing the network energy consumption while keeping high-quality service provision effectively is a critical requirement of future 5G networks, which has become a primary concern in achieving long-term green communication and self-sustainable operations with renewable energy in a resource-efficient way.

To achieve sustainable wireless communications, the energy harvesting (EH) technology has been introduced in wireless networks, which has attracted great attention from both academia and industry. The CO2 emission of future networks with EH capabilities will be potentially reduced by 20% [4]. The emerging radio access technologies (RAT) network with EH components that can capture ambient recyclable energy, (e.g., solar energy, RF energy and wind energy), are jointly considered to collect renewable energy as supplementary for the electric grid power [4], [5]. The implementation of renewable energy and energy efficient RATs can bring significant benefits by helping network operators to reduce energy costs

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and the burden of the electricity grid. Hence, it is desirable that wireless networks integrate EH capability, which breed new challenges for effective utilization of the harvested energy.

Recently, the integration of various multi-radio access technologies (multi-RAT) networks has been studied to address the challenges of the massive growth in mobile traffic demands, which plays vital roles to comprehensively improve wireless services from different aspects of 5G networks [6]. For instance, in order to effectively manage various devices in a large scale, an Internet of Things (IoT) system may integrate wireless networks adopting different RATs by means of Network Function Virtualization (NFV) and Software Defined Networking (SDN) [7]. In this manner, users could have connections to base stations (BSs) via different RATs, thus having seamless connectivity. Specifically, combined with the EH technology, the multi-RATs can harvest different amounts of energy in diverse environment. Then, energy consumption can be reduced effectively by leveraging energy between the multi-RATs, by means of coordinating RATs with overlapping coverage. However, the coexistence of multi-RAT networks requires efficient resource management algorithms of cross-RAT resource allocation to improve the energy efficiency.

Although EH-aided wireless networks have attracted recent attentions with potential advantages, they also introduce new design and management issues for multi-RAT network operators. First, since the harvested energy of surrounding environment depends heavily on environmental factors such as location and weather condition, the harvested energy will be quite unstable with environmental variations, due to the fact that the EH process is the characteristics of time-varying and strongly stochastic behaviors [8]. Furthermore, although multiple RATs co-exist in 5G networks, they are managed alone, which may lead to suboptimal utilization of overall network resources. For instance, RATs may be in disparate traffic load with different energy requirements, leading to the huge mismatch between harvested energy and traffic loads, which further degrades the resource utilization. Thus, the insufficiency and randomness of harvested energy without the priori knowledge of the energy result in the increasing network operating expenditure and unsatisfactory quality of services (QoS) of users. Furthermore, the aggregated resources on different RATs are underutilized to satisfy future requirements in the highly heterogeneous energy environment for energy-constrained 5G networks.

Therefore, to make full use of the harvested energy and overcome the huge mismatch situation between harvested energy supply and energy demand, an efficient resource-on-demand (ROD) energy management strategy with hybrid energy sources is necessarily needed, where the ROD strategy aims to scale the network capacity and energy to the actual network demand dynamically according to different QoS requirements of users. Cooperative energy scheduling between RATs is enabled, where the harvested energy can be transferred and shared flexibly by multi-RATs, in order to further improve the energy utilization. In addition, the data traffic and energy is distributed based on various factors such as traffic QoS requirements, the number of mobile devices, the type of service applications and the geographical environments. In order to fully exploit the availability of these resources considering the contextual environment information, the energy in multi-RATs should be cooperatively scheduled on demand and utilized with higher efficiency, for saving energy consumption and improving the network energy efficiency performance.

Research works have begun to study the renewable energy with the EH technology in wireless networks [4], [5], and the green-oriented resource allocation issues have also been investigated in [9], [10]. However, the existing works ignore the accumulation benefits and randomness of harvested energy in multi-RATs in the long term. Moreover, the previous works focused on the resource allocations based on perfect channel state information (CSI), neglecting the bursty of arrival data rates and the dynamics of CSI. Note that there are few works studying the EH technology in multi-RAT networks, which brings the urgent needs for studying renewable energy utilization and optimizing resource allocations in multi-RAT networks with heterogeneous energy sources.

In this paper, we propose a resource-on-demand allocation strategy for multi-RAT wireless networks, which are simultaneously powered by both harvested energy and grid power. By considering the dynamics of randomly varying harvested energy, dynamic traffic arrival and time-varying wireless channels, the flexible energy scheduling is formulated as a stochastic optimization problem to minimize the grid power consumption. Specifically, under the sporadic availability and discontinuity of the harvested energy, a dynamic network energy queue model is proposed to provide the enduring operation for resource optimization in multi-RAT wireless networks with renewable energy. Following the Lyapunov optimization framework, the stochastic optimization problem is transformed into a sequence of optimization subproblems, including the network flow control subproblem, the network energy management subproblem, and the network resource allocation subproblem. By solving these subproblems, an optimal resource-on-demand algorithm for multi-RAT wireless networks is developed to adapt to the dynamic environment. The main contributions of this paper are outlined as follows.

- We propose a resource-on demand strategy for flexible energy scheduling in multi-RATs with heterogeneous energy sources, where the harvested energy is effectively shared between RATs to satisfy varying energy demand.
- We propose a heterogenous energy supply model for the multi-RAT networks, which is powered by both the harvested energy and the grid energy. More specifically, we develop a realistic grid power cost model for the grid energy.
- We formulate the energy scheduling as a stochastic optimization problem to minimize the grid power cost. With the aid of Lyapunov framework, the dynamic adaptive resource-on-demand (DAROD) algorithm is proposed to accommodate the multi-dimension stochastic states in the dynamic environment. The grid power consumption can be effectively reduced with efficient utilization of harvested energy, where a priori distribution knowledge of the wireless channel and data arrival state is not required, which is very practical in real systems.

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- The tradeoff between grid power consumption and network delay is achieved, in which the increase of delay is approximately linear in $V$ and the decrease of grid power consumption is at the speed of $1/V$ with the control parameter $V$. It can provide guidelines for dynamic resource allocation in multi-RAT networks with heterogenous energy sources.

The remainder of the paper is organized as follows. The related work is presented in Section II. Section III gives the network model and problem formulation. The DAROD algorithm is given in Section IV. The tradeoff performance between network delay and network utility is investigated in Section V and Section VI. The proposed algorithm is verified by simulation results in Section VII. The conclusions are drawn in Section VIII.

## II. Related Works

*1) Allocation of Resources in Multi-RAT Networks:* The resource allocation problem in multi-RAT wireless networks has attached great attentions, which helps different RAT networks jointly improve their wireless resource utilization and network performances. It is well known that the orthogonal frequency division multiple access (OFDMA) technique has a strong robustness on frequency-selective fading channels, which is widely adopted in various wireless standards. For jointly allocating the subcarrier and power resource, a joint OFDMA-based iterative subcarrier and water filling power allocation algorithm was proposed in multi-RAT networks in [9]. A monotonic-based optimal approaching algorithm was proposed to maximize the sum rate and the number of scheduled non-prioritized links [11]. Nevertheless, the OFDMA-based allocation is with the binary variables and the resource allocation problem is formulated as a mixed integer nonlinear programming problem with prohibitive computational complexity. The mentioned literatures [9], [11] cannot obtain the optimal resource allocation solution. For deriving the optimal energy efficiency policy, a multiple-objective optimization problem was formulated to minimize the maximum of several quasiconvex fractional functions [12]. A decentralized parameter-free approach was developed to obtain the optimal multi-homing resource allocation efficiently in [13]. However, the EH technologies, which are promising to achieve green networking, are not considered in these works.

*2) EH Technique in Communication Systems:* The EH techniques have attracted significant attentions from both the industry and academia in recent years. To benefit the greenness from EH while overcoming the instability of renewable energy, a base station access and power control algorithm was developed to minimize the long-term average network service cost in [14]. A sustainable resource allocation was proposed to maximize the difference between the user utility gain and on-grid energy costs in cloud radio access networks which are powered by hybrid energy supplies [15]. An online dynamic transmission algorithm was developed in an energy harvesting communication system in [16]. A new relay selection and power allocation problem about selecting solar-powered relay station and grid-powered relay station was formulated as Mixed Integer Linear Programming to minimize the total grid power consumption in [17]. The tradeoff between throughput of small cell users and the associated power cost was optimized considering both energy harvesting constraints and interference constraints [18]. Under the heterogeneous energy supplies from renewable energy and electricity grid, a discrete time stochastic cross-layer optimization problem is formulated to maximize the time-average rate utility in [19]. In the schemes above, harvested energy is supplied only to its own use without energy cooperation. However, as the harvested energy is intermittent and sporadic, if a RAT is sheltered by the building or trees, the RAT's harvested energy will be not enough. Hence, this RAT will consume a lot of power resource from the grid energy. While, the RAT under good light condition may have too much harvested energy to consume, hence the remaining energy will disappear as heat. These inflexible designs [14]–[19] not only waste a lot of harvested energy but also consume more grid energy, which lead to huge mismatch between the dynamic traffic and renewable energy.

*3) Resource-on-Demand (ROD) Strategy:* The ROD strategy has been investigated by several works. For reducing the energy waste in dense wireless networks, a ROD strategy was developed to activate only the number of access points (AP) that is strictly needed with the actual traffic in [20]. An optimal power allocation problem was proposed to maximize the overall throughput based on non-orthogonal multiple access relay in multiple mobile users scenario in [21]. The higher coverage and capacity was achieved by using opportunistic carrier sense multiple access in multi-RAT networks [22]. A joint resource allocation scheme was proposed to minimizing the energy consumption while satisfying QoS performance requirements by the network cooperation in HetNets in [10]. For large scale wireless networks, an energy efficiency maximization problem on power allocation in wireless communication systems with multiple parallel channels was proposed in [23], [24]. However, all of these works are based on grid energy model, the jointly harvested energy and grid energy demand strategy has not been investigated yet.

## III. System Model and Problem Formulation

In this section, we first discuss the network model of multi-RAT wireless networks, which includes the heterogeneous energy supply model. The energy supply model and data queue model are also given herein. Then, we formulate the grid power consumption cost minimization as a stochastic optimization problem.

### A. System Model

In this paper, the tightly integrated multi-RAT wireless network scenario is considered as shown in Fig. 1. We assume that each UE is equipped with multiple radio capacity and it can access to the same core network through $N$ different RATs simultaneously. It should be noted that the inter-RAT interference can be relieved since different frequency bands are generally used for different RATs [11]. Let $\mathcal{N} = \{1, 2, \cdots, N\}$ and $\mathcal{U} = \{1, 2, \cdots, U\}$ denote the set of RATs

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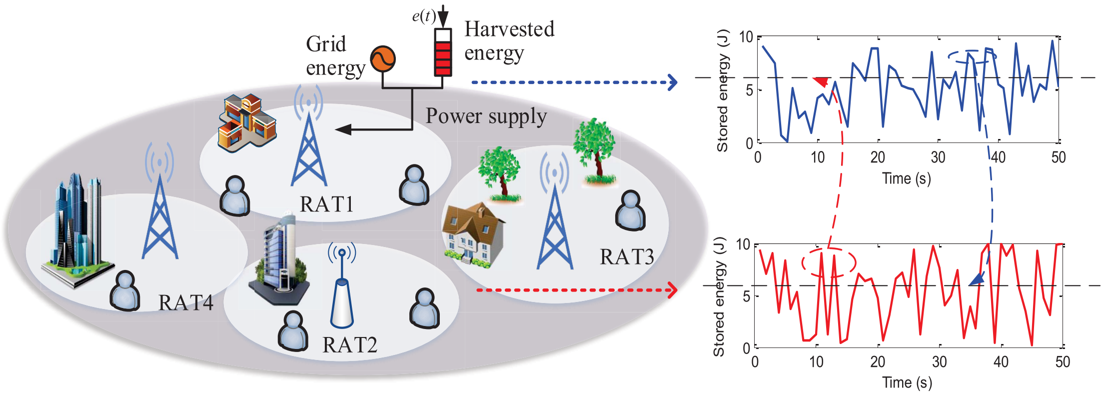


Fig. 1. System architecture of multi-RAT wireless network.

and UEs in multi-RAT wireless network, respectively. Due to the practical limits in multi-RAT capability, we consider that each UE $u$ (RAT $n$) can connect to the set of $\mathcal{N}_u$ RATs ($\mathcal{U}_n$ UEs) from the available RATs set $\mathcal{N}$ (UEs set $\mathcal{U}$), then $\mathcal{U} = \bigcup_{n=1}^{N} \mathcal{U}_n$, and $\mathcal{N} = \bigcup_{u=1}^{U} \mathcal{N}_u$.

We assume that the multi-RAT networks are operated in slotted time. The time-slots are normalized to integer values $t \in \{0, 1, 2, \cdots\}$. Under the deployment of OFDMA technology, the RATs need to allocate its subcarrier and transmit power resources to service the UEs that are connected to RATs. We define $J$ as the number of subcarriers with the set $\mathcal{J}$. $x_{n,u}^k(t)$ is the indicator function with binary variable to allocate subcarrier $k$ to UE $u$ in RAT $n$ at time-slot $t$. Let $g_{n,u}^k(t)$ be the channel gain for RAT $n$ to UE $u$ on subcarrier $k$ and $p_{n,u}^k(t)$ be the transmit power. We give the assumption that $\mathbf{g}(t) = [g_{n,u}^k(t)]_{n\in\mathcal{N}, u\in\mathcal{U}_n, k\in\mathcal{J}}$ is independently and identically distributed (i.i.d) over different time-slots in a finite state space $\mathcal{G}$. With the definition, the maximum achievable data rate of UE $u$ on subcarrier $k$ in RAT $n$ is calculated as follows,

$$b_{n,u}^k(t) = x_{n,u}^k(t) B_n \log_2\left(1 + \frac{|g_{n,u}^k(t)|^2 p_{n,u}^k(t)}{B_n N_0}\right), \quad (1)$$

where $B_n$ is the subcarrier spacing in RAT $n$, and $N_0$ is the power spectral density of additive white Gaussian noise. Due to the fact that each subcarrier can be only allocated to at most one UE in RAT $n$, we have

$$\sum_{u\in\mathcal{U}_n} x_{n,u}^k(t) \le 1, x_{n,u}^k(t) \in \{0,1\}, \forall k \in \mathcal{J}, t \ge 0. \quad (2)$$

Then, the sum rate of UE $u$ that is served by the RATs $\mathcal{N}_u$, is expressed as

$$R_u(t) = \sum_{n\in\mathcal{N}_u} b_{n,u}(t) = \sum_{n\in\mathcal{N}_u} \sum_{k\in\mathcal{J}} b_{n,u}^k(t). \quad (3)$$

where $b_{n,u}(t)$ is the transmission rate between RAT $n$ and UE $u$.

### *B. Energy Supply Model*

We assume that the multi-RAT is powered by heterogenous energy supply model that it can harvest energy from ambient energy sources (such as solar energy that considered in this paper) or purchase energy from the power grid. Different RATs

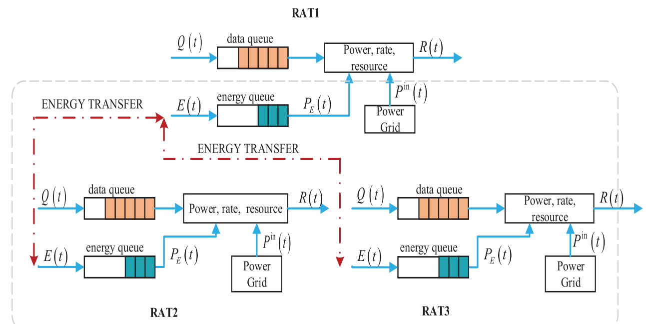


Fig. 2. Multi-RAT energy cooperation process.

are connected by the efficient cable. If the RAT is located with unfavorable climate conditions so it cannot have enough harvested energy, it can request harvested energy from other RATs whom harvest more than enough energy to feed itself with the energy transfer by the power grid. In addition, when the harvested energy in multi-RAT wireless network is not enough, the RAT should demand transmit power from the grid as shown in Fig. 1.

Let $P_n^{in}(t)$ denote the demand power from the grid at time slot $t$, and each RAT is equipped with a battery having the capacity $\theta_n^E$. There is $e_n(t)$ energy at time slot $t$ that is harvested by RAT $n$ from solar panels. Then, the demanded energy of different RATs should be no larger than that of the arrival which is constrained by

$$\sum_{m\in\mathcal{N}} \rho_{n,m}(t) \le 1, 0 \le \rho_{n,m}(t) \le 1, \forall n \in \mathcal{N}, \quad (4)$$

where $\rho_{n,m}(t)$ is the energy demand variable, which indicates that $\rho_{n,m}(t)$ fraction of harvested energy of RAT $n$ is demanded by RAT $m$.

Let $c_{n,m}$ denote the transmission discount of the harvested energy from RAT $n$ to RAT $m$, which satisfies that if $n = m$, $c_{n,m} = 1$; if $n \ne m$, $0 \le c_{n,m} < 1$. It shows that the RAT can use all energy harvested by itself, while the transmission loss will be caused if it demands energy from other RATs as shown in Fig. 2. The energy queuing dynamic equation is

$$E_n(t+1) = E_n(t) + P_n^{in}(t) + \sum_{m\in\mathcal{N}} c_{m,n}\rho_{m,n}e_m(t) - \sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}} x_{n,u}^k(t) p_{n,u}^k(t). \quad (5)$$

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where $E_n(t)$ denotes the energy queue size of RAT $n$ at time slot $t$. In practice, the transmit power of the RAT is bounded by the available energy in the network battery. Thus, we can obtain that the total transmission power of RAT $n$ is required as

$$\sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}} x^k_{n,u}(t)p^k_{n,u}(t) \leq E_n(t). \tag{6}$$

in each time slot $t$, the total amount of energy stored in battery is limited by the battery capacity, it should satisfy the inequality as

$$E_n(t) + P^{in}_n(t) + \sum_{m\in\mathcal{N}} c_{m,n}\rho_{m,n}e_m(t) \leq \theta^E_n. \tag{7}$$

Furthermore, in the multi-RAT wireless network, we assume that all of the RATs are supplied by one grid power, so that the total required grid transmit power should satisfy

$$\sum_{n\in\mathcal{N}} P^{in}_n(t) \leq P_{\max}. \tag{8}$$

Then, the maximum energy consumption of multi-RAT networks can be derived to $P_{\max}$.

### C. Data Queue Model

The amount of data arrival for UE $u$ at time slot $t$ (e.g., media content data) is modeled as a stochastic process $\mathcal{A}_u(t)$. With a finite state space $\Lambda$, we give the assumption that $\mathbf{A}(t) = [\mathcal{A}_u(t)]_{u\in\mathcal{U}}$ follows i.i.d at different time slots. In addition, the average arrival data rate of $\mathbf{A}(t)$ is denoted by $\boldsymbol{\lambda} = [\lambda_u]_{u\in\mathcal{U}}$, i.e., $\mathbb{E}[\mathcal{A}_u(t)] = \lambda_u, \forall u \in \mathcal{U}$. During time slot $t$, the amount of flow data of UE $u$ that arrived at RAT $n$ queue scheduler is denoted by $\gamma_{n,u}(t)$. Then, the following equation is satisfied

$$\sum_{n\in\mathcal{N}_u} \gamma_{n,u}(t) = \mathcal{A}_u(t), \forall u \in \mathcal{U}. \tag{9}$$

where RAT $n$ can provide an infinite buffer to store the data, and $Q_{n,u}(t)$ denotes the backlog for the data at time-slot $t$. During time-slot $t$, the data will be transmitted, which is stored in the buffer at the beginning of time-slot $t$. Hence, we describe the queue dynamics of $Q_{n,u}(t)$ $(\forall t > 0, n \in \mathcal{N}, u \in \mathcal{U}_n)$ as

$$Q_{n,u}(t+1) = \max[Q_{n,u}(t) - b_{n,u}(t), 0] + \gamma_{n,u}(t). \tag{10}$$

where the departure process is modeled as the first term in (10), the second term represents the arrival process. We can see that the arrival process of the queues and the departure process are stochastic due to the stochastic of $\mathbf{A}(t)$ and the time-varying characteristic of $\mathbf{g}(t)$. In addition, the queue backlogs of RATs are varying over time. Hence, it is necessary to make the model on queuing stability. The definition of the strongly stable condition is given as

*Definition 1: A queue is defined as strongly stable if the following inequality holds [25]:*

$$\lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}[Q_{n,u}(t)] < \infty. \tag{11}$$

According to the definition, we can call the queue as strongly stable if it has a bounded time average backlog. Then, the multi-RAT networks are called strongly stable since all individual queues of Multi-RAT network are strongly stable. Hence, we will use the term "stable" to refer to strongly stable in the following discussions.

*Remark 1: Based on the Little's Theorem, we can note that the average delay is proportional to the time averaged queue length [24]. Thus, the average delay can be depicted by the time averaged queue length which can also be described by network stability. In particular, it is a very important precondition to make resource allocation decisions in multi-RAT wireless networks.*

### D. Problem Formulation

For energy efficiency of multi-RAT networks, minimizing the grid energy consumption cost is an important design objective in wireless networks. In this paper, we will design the energy consumption cost as the performance metric, which is a convex increasing function of the demanded grid power $P^{in}_n(t)$. The electric grid power cost increases with the increase of the consumed electricity. In particular, we design the energy consumption cost $F_n$ as the performance metric with the form of $F_n(P^{in}_n(t)) = \kappa P^{in}_n(t)$, which is a convex increasing function of the demanded grid power $P^{in}_n(t)$ and the $\kappa$ is a positive constant parameter which depends on the actual grid price. Hence, we take the form of $F_n(P^{in}_n(t))$ in this paper for simplicity of formula derivation in the following section. It encourages the multi-RAT networks to consume more renewable energy than the grid energy. Mathematically, the stochastic programming problem $\mathcal{P}_1$ is formulated as

$$\begin{aligned}
&\min_{\boldsymbol{\gamma},\mathbf{x},\mathbf{p},\boldsymbol{\rho}} \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[F_n(P^{in}_n(t))]\\
&\text{s.t.}\quad \text{C1}: \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[Q_{n,u}(t)] < \infty, \quad \forall n\in\mathcal{N}, u\in\mathcal{U}_n,\\
&\qquad \text{C2}: \sum_{n\in\mathcal{N}_u}\gamma_{n,u}(t) = \mathcal{A}_u(t), \quad \forall u\in\mathcal{U},\\
&\qquad \text{C3}: \sum_{u\in\mathcal{U}_n} x^k_{n,u}(t) \leq 1, x^k_{n,u}(t)\in\{0,1\}, \quad \forall k\in\mathcal{J},\\
&\qquad \text{C4}: \sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}} x^k_{n,u}(t)p^k_{n,u}(t) \leq E_n(t), \quad \forall n\in\mathcal{N},\\
&\qquad \text{C5}: \sum_{n\in\mathcal{N}} P^{in}_n(t) \leq P_{\max},\\
&\qquad \text{C6}: \sum_{m\in\mathcal{N}} \rho_{n,m}(t) \leq 1, 0 \leq \rho_{n,m}(t) \leq 1, \quad \forall n\in\mathcal{N},\\
&\qquad \text{C7}: E_n(t) + P^{in}_n(t) + \sum_{m\in\mathcal{N}} \rho_{m,n}c_{m,n}e_m(t) \leq \theta^E_n, \forall n\in\mathcal{N},
\end{aligned} \tag{12}$$

where C1 is the multi-RAT network stability constraint, C2 shows that rate-aggregation received at the UE should be equal to the arrival, C3 is the subcarrier resource constraint, C4 shows that the total energy consumption at RAT $n$ should be smaller than the available energy at the battery of the

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RAT, C5 shows that the demanded energy of the RATs should be smaller than the grid power, C6 shows that the demanded renewable energy by RATs should be smaller than the harvested energy from the solar panels and C7 is the battery capacity constraint.

The stochastic problem $\mathcal{P}_1$ has the constraint that coupled with both the time-averaged requirements and instantaneous constraints which are performed at each time-slot. Hence, due to the the randomly varying energy state information (ESI), dynamic queue state information (QSI) and time-varying wireless channel state information (CSI), problem (12) can be viewed as a stochastic problem, which is quite difficult to achieve the optimal solution. Then, a solution is the approach for finding flow rate $\boldsymbol{\gamma}(t) = [\gamma_{n,u}(t)]_{n\in\mathcal{N},u\in\mathcal{U}_n}$, subcarrier variable $\mathbf{x} = [x^k_{n,u}]_{n\in\mathcal{N},u\in\mathcal{U}_n,k\in\mathcal{J}}$, transmit power $\mathbf{p}(t) = [p^k_{n,u}(t)]_{n\in\mathcal{N},u\in\mathcal{U}_n,k\in\mathcal{J}}$ and the demand variable $\boldsymbol{\rho}(t) = [\rho_{n,m}(t)]_{n,m\in\mathcal{N}}$, $\mathbf{P}(t) = [P_n(t)]_{n\in\mathcal{N}}$ over time according to the dynamic network state, which minimizes the grid power cost while all the constraints are satisfied.

It is known that problem (12) includes multiple management components, i.e. network flow control, resource allocation, data queue management and energy management. Besides that, by solving problem (12), the inherent tradeoff between electricity grid power cost and network delay is derived in the following sections.

## IV. Algorithm Design for Multi-RAT Resource Allocation

As mentioned above, we can see that problem $\mathcal{P}_1$ is a stochastic optimization problem that cannot be directly solved by convex optimization approach. To solve optimization problem $\mathcal{P}_1$, we take the advantage of Lyapunov optimization technique [25] to design a dynamic optimization approach, which can decompose problem $\mathcal{P}_1$ into three subproblems, i.e. network flow control, resource allocation and energy management subproblems, respectively. With the aid of Lyapunov optimization approach, the adaptive resource allocation algorithm is proposed to accommodate the dynamic wireless networks only according to the current QSI and CSI,[1] making the algorithm easily implemented in practice by solving the three subproblems.

Motivated from the Lyapunov optimization with weight perturbation technique in [25], we introduce the weight perturbation $\theta^E_n$, which is taken by the limited battery capacity of RAT $n$ defined in Section II. We note that $\mathbf{Q}(t)$ and $\mathbf{E}(t)$ are the matrixs including the data queue $\{Q_{n,u}(t)|\forall n\in\mathcal{N}, u\in\mathcal{U}_n\}$ and energy queue $\{E_n(t)|\forall n\in\mathcal{N}\}$, respectively. Then, the multi-RAT network state at time slot $t$ is defined as $\mathbf{Z}(t)\triangleq(\mathbf{Q}(t),\mathbf{E}(t))$. We then define the quadratic Lyapunov function as

$$L(\mathbf{Z}(t)) = \frac{1}{2}\sum_{n\in\mathcal{N}}\sum_{u\in\mathcal{U}_n} Q^2_{n,u}(t) + \frac{1}{2}\sum_{n\in\mathcal{N}}(E_n(t)-\theta^E_n)^2. \tag{13}$$

where $L(\mathbf{Z}(t))$ is a nonnegative scalar measure of these states, and the system will toward to unstable states when the Lyapunov function grows large. Then, the system stability can be achieved by making the Lyapunov function drift in the negative direction towards zero. Hence, For achieving the stability, minimizing the quadratic Lyapunov function can push the energy queue towards the corresponding perturbed variable value, and the data queue towards zero, respectively.

Then, at time slot $t$, the conditional expected Lyapunov drift of the network is given by

$$\Delta(\mathbf{Z}(t)) :\triangleq \mathbb{E}[L(\mathbf{Z}(t+1))|\mathbf{Z}(t)] - \mathbb{E}[L(\mathbf{Z}(t))], \tag{14}$$

where the expectation $\mathbb{E}[\cdot]$ is taken over the randomness of departure and arrival processes of the data queue and the energy queue, respectively. The penalty term $V\mathbb{E}[F_n(P^{in}_n(t)|\mathbf{Z}(t)]$ is added to (14) for achieving the *drift-plus-penalty* term with the Lyapunov optimization framework as follows,

$$\Delta_V(\mathbf{Z}(t)) = \Delta(\mathbf{Z}(t)) + V\mathbb{E}[F_n(P^{in}_n(t)|\mathbf{Z}(t)]. \tag{15}$$

where $V > 0$ is a control parameter, which can be regard as the non-negative weight that is chosen as desired to affect a performance tradeoff. The practical meaning of $V$ will be given in Section V. Furthermore, regarding the *drift-plus-penalty* term, we have the lemma as follows.

*Lemma 1: At time-slot $t$, given the feasible resource allocation decision that can be taken, we have*

$$\begin{aligned}\Delta_V(\mathbf{Z}(t)) \le\ &\hat{\Theta} + V\sum_{n\in\mathcal{N}} F_n(P^{in}_n(t)) \\ &+ \sum_{n\in\mathcal{N}}\sum_{u\in\mathcal{U}_n} Q_{n,u}(t)(\gamma_{n,u}(t) - b_{n,u}(t)) \\ &+ \sum_{n\in\mathcal{N}}(E_n(t)-\theta^E_n)\Big(P^{in}_n(t) + \\ &+ \sum_{m\in\mathcal{N}} c_{m,n}\rho_{m,n}e_m(t) - \sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}} x^k_{n,u}(t)p^k_{n,u}(t)\Big)\end{aligned} \tag{16}$$

*where $\hat{\Theta}$ is an upper bound on the term $\frac{1}{2}[\mathbf{b}(t)^H\mathbf{b}(t) + \boldsymbol{\gamma}(t)^H\boldsymbol{\gamma}(t)]$.*

*Proof:* This proof is given in Appendix A.

Based the analysis above, the dynamic resource allocation can be motivated as follows. First, we aim to make $(\mathbf{Z}(t))$ smaller to push data queue backlog toward a lower data queue length, guaranteeing that (11) holds. Second, the $\mathbb{E}[F_n(P^{in}_n(t)|\mathbf{Z}(t)]$ should also been reduced without causing large grid power cost, minimizing the objective of problem $\mathcal{P}_1$ at the same time. From the given analysis, our dynamic resource allocation policy is designed to make the resource allocation decisions for minimizing the right hand side of (15), which can be decomposed into a series of independent subproblems and can be solved concurrently with the current network state information (ESI, CSI and QSI at the current time).

### A. Multi-RAT Flow Control

The optimal multi-RAT flow rate can be obtained by minimizing the first item of R.H.S of (16) at each time slot. Due to the fact that the flow rate variables of multi-RAT flow

[1]The current information about QSI and CSI is usually assumed as perfect.

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control problem $\mathcal{P}_{\mathcal{FC}}$ are independent among different UEs, the minimization of flow rate can be computed for each UE separately as

$$\begin{aligned}\mathcal{P}_{\mathcal{FC}}: \min \sum_{n\in\mathcal{N}} Q_{n,u}(t)\gamma_{n,u}(t)\\ \text{s.t.} \sum_{n\in\mathcal{N}_u} \gamma_{n,u}(t) = \mathcal{A}_u(t).\end{aligned} \tag{17}$$

We can see that the optimal multi-RAT flow control solution consists of choosing the RAT with the smallest queue backlog $Q_{n,u}(t)$, and assigning the entire requested traffic $\mathcal{A}_u(t)$, respectively.

### B. Multi-RAT Energy Management

Furthermore, the energy management subproblem $\mathcal{P}_{\mathcal{EM}}$ can be obtained by combining the second term of the R.H.S of (16) with constraints C5-C7, which is formulated as

$$\begin{aligned}\min\ & V\sum_{n\in\mathcal{N}} F_n(P_n^{in}(t)) + \sum_{n\in\mathcal{N}}(E_n(t)-\theta_n^E)P_n^{in}(t)\\ &+\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{N}}(E_n(t)-\theta_n^E)c_{m,n}\rho_{m,n}(t)e_m(t)\\ \text{s.t.}\ & \text{C5}: \sum_{n\in\mathcal{N}} P_n^{in}(t)\le P_{\max},\\ & \text{C6}: \sum_{m\in\mathcal{N}}\rho_{n,m}(t)\le 1, 0\le\rho_{n,m}(t)\le 1, \quad \forall n\in\mathcal{N},\\ & \text{C7}: E_n(t)+P_n^{in}(t)+\sum_{m\in\mathcal{N}}\rho_{m,n}c_{m,n}e_m(t)\le\theta_n^E, \ \forall n\in\mathcal{N}.\end{aligned} \tag{18}$$

The energy management subproblem $\mathcal{P}_{\mathcal{EM}}$ is composed of renewable energy harvesting and energy demand processes. Furthermore, all of the harvested energy will be stored by the RATs if they have enough capacity in the battery buffer according to the battery capacity $\theta_n^E$. More specifically, $(E_n(t)-\theta_n^E)c_{m,n}$ is considered as the allocation weight of the arrival harvested energy $e_m(t)$. Besides that, the RATs can demand energy from the grid power system when the harvested energy is insufficient. Therefore, the energy management decisions $P_n^{in}(t)$ and $\rho_{m,n}(t)$ are jointly determined under the current ESI and QSI which are known at the same time. Due to the fact that the objective function of problem $\mathcal{P}_{\mathcal{EM}}$ is the difference of convex function and linear function, and that all of the constraints in (19) is linear, so the energy management subproblem is a convex optimization in $(P_n^{in}(t), \rho_{m,n}(t))$. The efficient algorithm will be studied in the next section.

### C. Multi-RAT Resource Allocation

By observing (16), the optimal joint subcarrier and power allocation of at time slot $t$ can be achieved by maximizing the remaining item of R.H.S of (16), which is given by

$$\begin{aligned}\mathcal{P}_{\mathcal{RA}}: \max\ & \sum_{n\in\mathcal{N}}\sum_{u\in\mathcal{U}_n} Q_{n,u}(t)b_{n,u}(t)\\ &-\sum_{n\in\mathcal{N}}\sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}}(E_n(t)-\theta_n^E)x_{n,u}^k(t)p_{n,u}^k(t)\\ \text{s.t.}\ & \text{C3}: \sum_{u\in\mathcal{U}_n} x_{n,u}^k(t)\le 1, x_{n,u}^k(t)\in\{0,1\}, \forall k\in\mathcal{J},\\ & \text{C4}: \sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}} x_{n,u}^k(t)p_{n,u}^k(t)\le E_n(t), \forall n\in\mathcal{N},\end{aligned} \tag{19}$$

This subproblem is a mixed-integer non-linear convex programming and it is usually prohibitively difficult to solve. Although the similar problems have been studied in [9], [26], which optimized the subcarrier and power allocation separately, suffering from highly computational complexity. To address this challenge, we will propose an efficient algorithm in the next section.

## V. Optimal Energy Management and Resource Allocation

In this section, we aim to propose effective approaches to solve the subproblems of energy management and resource allocation in multi-RAT networks, respectively. The continuity relaxation of binary variables will be used and Lagrange dual decomposition method will be taken. The optimal solutions of the two subproblems are then obtained. As the two subproblems are optimized at each time slot, the slot index $t$ will be ignored for brevity.

### A. Solution of Multi-RAT Energy Management

By observing subproblem $\mathcal{P}_{\mathcal{EM}}$, we relax the variable $\rho_{m,n}$ to the continuous interval $[0,1]$, then subproblem $\mathcal{P}_{\mathcal{EM}}$ becomes a convex optimization problem. The transformed problem $\mathcal{P}_{\mathcal{EM}}$ is concave and the constraints of it are linear inequalities. Thus, according to the Salter's condition, the zero Lagrange duality gap in this problem can be guaranteed [27]. Relaxing the constraints C5 and C6 by $\sigma$ and $\nu_n$, respectively, the Lagrangian function of subproblem $\mathcal{P}_{\mathcal{EM}}$ can be expressed as

$$\begin{aligned}L(\mathbf{P},\boldsymbol{\rho},\boldsymbol{\sigma},\boldsymbol{\nu}) =& V\sum_{n\in\mathcal{N}} F_n(P_n^{in})+\sum_{n\in\mathcal{N}}(E_n-\theta_n^E)P_n^{in}\\ &+\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{N}}(E_n-\theta_n^E)c_{m,n}\rho_{m,n}e_m\\ &-\sum_{n\in\mathcal{N}}\nu_n\left(E_n+P_n^{in}+\sum_{m\in\mathcal{N}}\rho_{m,n}c_{m,n}e_m-\theta_n^E\right)\\ &-\sigma\left(\sum_{n\in\mathcal{N}} P_n^{in}-P_{\max}\right).\end{aligned} \tag{20}$$

Let $\Phi(P_n^{in}) = VF_n(P_n^{in})+(E_n-\theta_n^E)P_n^{in}-\nu_nP_n^{in}-\sigma P_n^{in}$, and $\Lambda_{n,m}=(E_n-\theta_n^E-\nu_n)c_{m,n}e_m$, the corresponding Lagrange dual is

$$\begin{aligned}d(\boldsymbol{\sigma},\boldsymbol{\nu}) = \min_{\mathbf{P},\boldsymbol{\rho}}&\left\{\begin{array}{c}\sum_{n\in\mathcal{N}}\Phi(P_n^{in})+\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}\Lambda_{n,m}\rho_{n,m}\\ -\sum_{n\in\mathcal{N}}\nu_nE_n+\sum_{n\in\mathcal{N}}\nu_n\theta_n^E+\sigma P_{\max}\end{array}\right\}\\ \text{s.t.}&\sum_{n\in\mathcal{N}}\rho_{n,m}\le 1, 0\le\rho_{n,m}\le 1, \forall n\in\mathcal{N}.\end{aligned} \tag{21}$$

The equation above is a classical linear assignment problem for energy demand variable $\rho_{m,n}$. Then, the optimal solution is

$$\rho_{m,n} = \begin{cases}1, & n=\operatorname{argmin}_l\{\Lambda_{l,m}, \forall l\in\mathcal{N}\}\\ 0, & \text{otherwise.}\end{cases} \tag{22}$$

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Given the optimal energy demand variable $\rho_{m,n}$, the minimization of the problem in (21) can be achieved by finding the partial derivative of $\Phi(P_n^{in})$ with respect to $P_n^{in}$, which is given by

$$\frac{\partial \Phi(P_n^{in})}{P_n^{in}} = VF_n'(P_n^{in}) + E_n - \theta_n^E - \nu_n - \sigma. \quad (23)$$

Hence, the optimal grid power is given as

$$P_n^{in} = F_n^{-1}(\frac{\theta_n^E + \nu_n + \sigma - E_n}{V}). \quad (24)$$

Then, the dual problem of (18) is formulated as

$$\begin{aligned} \max \quad & d(\boldsymbol{\sigma}, \boldsymbol{\nu}) \\ \text{s.t.} \quad & \sigma \geq 0, \nu \geq 0, \end{aligned} \quad (25)$$

which is always a concave optimization problem. Therefore, the gradient descent method can be used to calculate the optimal values for $\sigma$ and $\nu$ [27], i.e.

$$\begin{aligned} \sigma(\iota+1) &= \sigma(\iota) - \mu\left(\sum_{n\in\mathcal{N}} P_n^{in}(\iota) - P_{\max}\right). \\ \nu(\iota+1) &= \nu(\iota) - \varpi\left(E_n + P_n^{in}(\iota) + \sum_{m\in\mathcal{N}} \rho_{m,n}(\iota) c_{m,n} e_m - \theta_n^E\right). \end{aligned} \quad (26)$$

In the equations above, $\iota$ is an iteration index, $\mu$ and $\varpi$ are the sufficiently small step sizes. Due to the fact that the gradient of (23) satisfies the Lipchitz continuity condition, the convergence of the iteration in (19) towards the optimal $\sigma$ and $\nu$ is guaranteed [28].

### B. Solution of Multi-RAT Resource Allocation

In this subsection, the continuity relaxation of binary variables and the Lagrange dual decomposition method are used to solve the resource allocation problem $\mathcal{P}_{\mathcal{RA}}$.

*1) Continuity Relaxation and Convexification:* First, we relax $x_{n,u}^k$ to the continuous interval $[0,1]$, we introduce a new variable $s_{n,u}^k = x_{n,u}^k p_{n,u}^k$ for each UE $u$ and subcarrier $k$. Then, we can rewrite the resource allocation subproblem as

$$\begin{aligned} \max \quad & \sum_{n\in\mathcal{N}} \sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} Q_{n,u} x_{n,u}^k B_n \log_2\left(1 + \frac{|g_{n,u}^k|^2 s_{n,u}^k}{x_{n,u}^k B_n N_0}\right) \\ & - \sum_{n\in\mathcal{N}} \sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} (E_n - \theta_n^E) s_{n,u}^k \\ \text{s.t.} \quad & \sum_{u\in\mathcal{U}_n} x_{n,u}^k \leq 1, 0 \leq x_{n,u}^k \leq 1, \forall k \in \mathcal{J}, \\ & \sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} s_{n,u}^k \leq E_n, \forall n \in \mathcal{N}, \\ & s_{n,u}^k \geq 0, \forall n \in \mathcal{N}, u \in \mathcal{U}_n, k \in \mathcal{J}. \end{aligned} \quad (27)$$

We can see that problem (27) is concave, because it is the difference of a concave log function and a linear function. In addition, since the feasible sets of the constraints are linear, the Slater's condition is always satisfied, so a zero Lagrange duality gap can be achieved [27].

*2) Lagrange Dual Solution:* We relax the RAT battery constraint by introducing dual variables $\omega_n$. Then, we obtain the following Lagrange function as

$$\begin{aligned} L(\mathbf{s}, \mathbf{x}, \boldsymbol{\omega}) =& \sum_{n\in\mathcal{N}} \sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} Q_{n,u} x_{n,u}^k B_n \log_2\left(1 + \frac{|g_{n,u}^k|^2 s_{n,u}^k}{x_{n,u}^k B_n N_0}\right) \\ & - \sum_{n\in\mathcal{N}} \sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} (E_n - \theta_n^E) s_{n,u}^k \\ & - \sum_{n\in\mathcal{N}} \omega_n \left(\sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} s_{n,u}^k - E_n\right) \end{aligned} \quad (28)$$

Then, the dual function is given as

$$\begin{aligned} d(\boldsymbol{\omega}) = \min_{\mathbf{s},\mathbf{x}} \quad & L(\mathbf{s}, \mathbf{x}, \boldsymbol{\omega}) \\ \text{s.t.} \quad & \sum_{u\in\mathcal{U}_n} x_{n,u}^k \leq 1, 0 \leq x_{n,u}^k \leq 1, \forall k \in \mathcal{J}, \end{aligned} \quad (29)$$

and the dual problem of (27) is formulated as

$$\begin{aligned} \min \quad & d(\boldsymbol{\omega}) \\ \text{s.t.} \quad & \boldsymbol{\omega} \geq 0. \end{aligned} \quad (30)$$

It is well known that the minimum problem (30) is identical to the maximum problem (27). Thus, problem can be solved by finding the optimum $\boldsymbol{\omega}$.

We take the Karush-Kuhn-Tucker (KKT) conditions for problem (30), we can have

$$s_{n,u}^k = \left[\frac{Q_{n,u} B_n}{(E_n - \theta_n + \omega_n)\ln 2} - \frac{B_n N_0}{g_{n,u}^k}\right]^+ x_{n,u}^k, \quad (31)$$

where $[x]^+ = \max\{0, x\}$.

Furthermore, we take (31) into (28) and let

$$\begin{aligned} \Lambda_{n,u}^k &= Q_{n,u} B_n \log_2\left(1 + \frac{|g_{n,u}^k|^2}{B_n N_0}\left[\frac{Q_{n,u} B_n}{(E_n - \theta_n + \omega_n)\ln 2} - \frac{B_n N_0}{g_{n,u}^k}\right]^+\right) \\ & - (E_n - \theta_n^E)\left[\frac{Q_{n,u} B_n}{(E_n - \theta_n + \omega_n)\ln 2} - \frac{B_n N_0}{g_{n,u}^k}\right]^+ \\ & - \omega_n \left[\frac{Q_{n,u} B_n}{(E_n - \theta_n + \omega_n)\ln 2} - \frac{B_n N_0}{g_{n,u}^k}\right]^+, \end{aligned} \quad (32)$$

we finally rewrite (30) as

$$\begin{aligned} d(\boldsymbol{\omega}) = \min_{\mathbf{x}} \quad & \sum_{n\in\mathcal{N}} \sum_{u\in\mathcal{U}_n} \sum_{k\in\mathcal{J}} \Lambda_{n,u}^k x_{n,u}^k + \sum_{n\in\mathcal{N}} \omega_n E_n \\ \text{s.t.} \quad & \sum_{u\in\mathcal{U}_n} x_{n,u}^k \leq 1, 0 \leq x_{n,u}^k \leq 1, \forall k \in \mathcal{J}, \end{aligned} \quad (33)$$

The problem can be considered as a classical linear assignment problem. The optimal $x_{n,m_l}^k$ can only be obtained among extreme points in the constraint set (i.e., 0 or 1). Therefore, the optimal solution is still binary after continuity relaxation on $x_{n,m_l}^k$. More specifically, the allocation of $\mathbf{x}$ is only determined by $\Lambda_{n,m_l}^k$. Thus, for any subcarrier $k \in \mathcal{J}_n$, $x_{n,m_l}^k$, where $m_l = \text{argmax}_{m_l \in M_n}\{\Lambda_{n,m_l}^k, \forall k \in \mathcal{J}_n, n \in \mathcal{N}\}$, the best subcarrier allocation is shown as follows.

$$x_{n,m_l}^k = \begin{cases} 1, & m_l = \underset{m_l\in M_n}{\text{argmax}}\{\Lambda_{n,m_l}^k, \forall k \in \mathcal{J}_n, n \in \mathcal{N}\}; \\ 0, & \text{otherwise}. \end{cases} \quad (34)$$

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Because $s^k_{n,m_l} = x^k_{n,m_l} p^k_{n,m_l}$, after computing the optimal subcarrier allocation $\mathbf{x}^*$, the optimal power allocation $\mathbf{p}^*$ can be obtained from (28).

The optimal values of $\boldsymbol{\omega}^*$ is determined by solving dual problem (30). By using a gradient descent method, the optimal values of $\boldsymbol{\omega}^*$ is given by

$$\omega_n^{\iota+1} = \left[\omega_n^{\iota} + \varrho\left(\sum_{u\in\mathcal{U}_n}\sum_{k\in\mathcal{J}} x^k_{n,u}p^k_{n,u} - E_n\right)\right]^+, \quad (35)$$

where $[\cdot]^+$ is defined as the projection of $[\cdot]$ onto the non-negative orthant and $\varrho$ denotes the sufficiently small positive step-sizes. With some sufficiently small step-sizes, the gradient descent method can converge to the optimal Lagrange multiplier [28].

*3) Optimality With Respect to Resource Allocation:* In this step, we show that the continuity relaxation and Lagrange dual method lead to the optimal subcarrier and power allocations for optimizing problem (19).

We note that the problem (27) is a relaxed version for optimizing problem (19), so the optimum of (29) should be smaller than that of problem (27). Furthermore, the constraints C3 and C4 can be satisfied by the optimal solution of the continuity relaxed problem (27). We then state that the optimum of problem (27) is also the optimum of problem (19).

*4) Computational Complexity:* In (31), the dual problem (28) is solved by the subgradient method. To achieve $\delta$-optimality, i.e., $|d(\boldsymbol{\omega})-d(\boldsymbol{\omega}^*)| < \delta$, the number of iterations is on the order of $O(1/\delta^2)$ [27]. In each iteration, (31) needs to be computed for $J$ subcarriers. Because that there are $N \times |\mathcal{U}_n|$ connections in the multi-RAT networks. In each iteration, (31) needs to be operated $N \times |\mathcal{U}_n|$ times. So the computational complexity for computing (31) is taken as $O(N \times |\mathcal{U}_n|)$. Therefore, the computational complexity of dynamic resource allocation is $O\left((N \times |\mathcal{U}_n|)(1/\delta^2)\right)$. Finally, the overall procedure of the DAROD algorithm is summarized in **Algorithm 1**.

**Algorithm 1** Dynamic Adaptive Resource-on-Demand (DAROD) Algorithm

**Step 1:** For each time slot $t$, observe the current QSI $Q_{n,u}(t)$ and ESI $E_n(t)$;
**Step 2 (Multi-RAT Network Flow Control):** Calculate the optimal flow control variable $\gamma_{n,u}(t)$ according to (17);
**Step 3 (Multi-RAT Network Energy Management):**
**repeat**
  Obtain the energy demand variable $\rho_{m,n}(t)$ according to (21);
  Obtain the grid power $P^{in}_n(t)$ according to (24);
  Update the Lagrangian dual variables $\sigma$ and $\nu$ according to (26);
**until** Certain stopping criteria is met;
**Step 4 (Multi-RAT Network Resource Allocation):**
**repeat**
  Obtain the subcarrier allocation variable $x^k_{n,u}(t)$ according to (34);
  Obtain the subcarrier power $p^k_{n,u}(t)$ according to (31);
  Update the Lagrangian dual variable $\omega$ according to (35);
**until** Certain stopping criteria is met;
**Step 5:** Updates the data queues $Q_{n,u}(t)$ and the energy queues $E_n(t)$.

## VI. Tradeoff Performance Between Power Consumption Cost and Delay

In this section, we will mathematically analyze the performance bounds of the proposed DAROD algorithm based on Lyapunov optimization. Firstly, we give the following bound assumptions and concepts, which will be used in the performance discussion.

Firstly, we note that $s(t) = (\mathbf{A}(t), \mathbf{g}(t), \mathbf{E}(t)) \in \mathcal{S}$ and $\alpha(t) = (\boldsymbol{\gamma}(t), \mathbf{x}(t), \mathbf{p}(t), \boldsymbol{\rho}(t)) \in \Omega$ represent the network state and the network decision at time slot $t$, where $\Omega$ is the set of feasible network decisions and $\mathcal{S}$ is the network sate space [29]. Based on the property of boundness of transmit power $\mathbf{p}(t)$ and the fact of all physical quantities in realistic systems, the electricity cost satisfies

$$F_{\min} \le \mathbb{E}[F_n(P^{in}_n(t))] \le F_{\max}, \quad (36)$$

where $F_{\min}$ and $F_{\max}$ are some finite constants.

Specifically, aiming to minimize the current electricity cost $F_n(P^{in}_n(t))$ under the constraints (C2)-(C7), $s$-only policy is defined as a stationary policy and possibly randomized function of the current state $s(t)$ only that choose action $\tilde{\alpha}(t)$ independently at every time-slot. With $s$-only policy, the expectation of the flow rates and network rates are the same for all time slots due to the stationary distribution of $s(t)$. Then, the following lemma is given(the proof is omitted due to the limited space) [30].

*Lemma 2: If $\boldsymbol{\lambda}$ is strictly interior to the capacity region $\Lambda$, $\boldsymbol{\lambda} + \varsigma$ is still in $\Lambda$ for a positive $\varsigma$, an $s$-only policy can be found that*

$$\mathbb{E}\left[\tilde{b}_{n,m}(t)(\tilde{\alpha}(t), s(t))\right] \ge \varsigma + \mathbb{E}\left[\tilde{\gamma}_{n,m}(t)(\tilde{\alpha}(t), s(t))\right], \quad (37)$$

*where $\tilde{b}_{n,m}(t)$ and $\tilde{\gamma}_{n,m}(t)$ denote the resulting values under $s$-only policy [30].*

*Proof:* Based on the capacity region which is defined as all of the average traffic arrival rates $\boldsymbol{\lambda}$ that can be stably supported by the Multi-RAT networks, we can obtain that a resource allocation policy can be founded with the constraint of the average traffic arrival rate $\boldsymbol{\lambda}$ [30]. We define $\tilde{\alpha}(t)$ as the transmission decision under a particular $s$-only policy, and define $\tilde{b}_{n,m}(t)$ and $\tilde{\gamma}_{n,m}(t)$ as the resulting values under $s$-only policy on time slot $t$. Therefore, for any vector $\Lambda$, there exists an $s$-only policy that satisfies as $\mathbb{E}\left[\tilde{b}_{n,m}(t)(\tilde{\alpha}(t), s(t))\right] \ge \mathbb{E}\left[\tilde{\gamma}_{n,m}(t)(\tilde{\alpha}(t), s(t))\right] + \varsigma$. ■

The performance of the proposed DAROD algorithm can be obtained based on **Lemma 2**.

*Theorem 1: For any network control parameter $V > 0$, if $\boldsymbol{\lambda} + \varsigma$ is strictly in the capacity region $\Lambda$ of the multi-RAT and $\mathbb{E}[L(\mathbf{Z}(0))] < \infty$, the properties of proposed DAROD algorithm can be achieved [30]:*

*a) $\overline{F}^{pro}$ is time averaged power consumption cost and $\overline{F}^{opt}$ is the optimal value for solving the original problem, we can*

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*have that*

$$\overline{F}^{pro} \geq \overline{F}^{opt} - \frac{\hat{\Theta}}{V}. \quad (38)$$

*b) The proposed algorithm guarantees that all data queues in the Multi-RAT networks are stable with $V \geq 0$. The time averaged queue length is bounded by*

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}_n} \mathbb{E}[Z_{n,m}(t)] \leq \frac{\hat{\Theta} + V(F_{\max} - \overline{F}^{opt})}{\varsigma}. \quad (39)$$

*Proof:* The proof is omitted due to limited space. ■

Firstly, based on the property (a) of **Theorem 1**, the time averaged power consumption cost $\overline{F}^{pro}$ decreases at the speed of $\mathcal{O}(1/V)$ with a decay rate of $\hat{\Theta}/V$ when $V$ increases, and $\overline{F}^{pro}$ of the proposed algorithm is arbitrarily close to $\overline{F}^{opt}$ when setting a sufficiently large $V$. It means that the proposed algorithm is asymptotically optimal for solving the problem. Hence, the proposed algorithm can fully utilize the harvested and grid power energy with a sufficiently large $V$ in multi-RAT networks.

Secondly, the performance bound of the time averaged data queue length is shown in the property (b) of **Theorem 1**. It shows that the time averaged data queue length is proportional to the network control parameter $V$ at the speed of $\mathcal{O}(V)$. The time averaged delay of time averaged data queue length can be depicted based on the fact that the average transmission delay of data transmission is proportional to the average queue length from Little's Theorem [28]. Specifically, a larger $V$ value results in a larger time averaged data queue length but a less time averaged power consumption cost. Hence, it proves that there exists a $\mathcal{O}(\frac{1}{V}), \mathcal{O}(V)$ tradeoff between the time averaged data queue length and the time averaged power consumption cost, which provides an efficient approach to control cost-delay performance to satisfy the QoS requirements of multi-RAT design and the demands of effective resource allocation adaptively.

## VII. Simulation Results

In this section, the simulation results are presented to evaluate the performance of the proposed algorithm and verify our theoretical analysis in the multi-RAT wireless networks powered by heterogeneous energy sources. In the simulation, we consider multi-RAT wireless networks constituted by three RATs. The transmission over wireless channels between RATs and UEs are orthogonal, thus, there is no interference among them. the CSI is assumed to be independent and identically distributed (i.i.d) across different time slots [31]. The channel gain between RAT $n$ and UE $u$ are $g_{n,u}(t)$ is independently and identically distributed (i.i.d) over different time slots, and $\mathbf{g}(t)$ takes values in a finite state space $\mathcal{G}$ which is uniformly distributed over [4,10]. The value of QoS requirement represents a measure of the distance between the rate vector and the capacity region boundary. In addition, the greedy algorithm with maximum transmission power is taken as the benchmark algorithm. Without special statement, the simulation parameters are set according to Table I and some special parameters will be specified in each numerical experiment if necessary.

TABLE I

KEY PERFORMANCE INDICATORS

| **Parameters** | **Values** |
|---|---|
| Number of RATs | 3 |
| Bandwidth of RAT1 | 20MHz |
| Bandwidth of RAT2 | 20MHz |
| Bandwidth of RAT3 | 20MHz |
| Number of Users | [40,60] |
| Noise Power | -174 dBm/Hz |
| data buffer size | 1000 (bit) |
| Network Battery Capacity | 200 (Wh) |
| harvested energy | U(0,80) W |
| QoS requirements | 1, 2, 3 (bit/HZ/time-slot) |

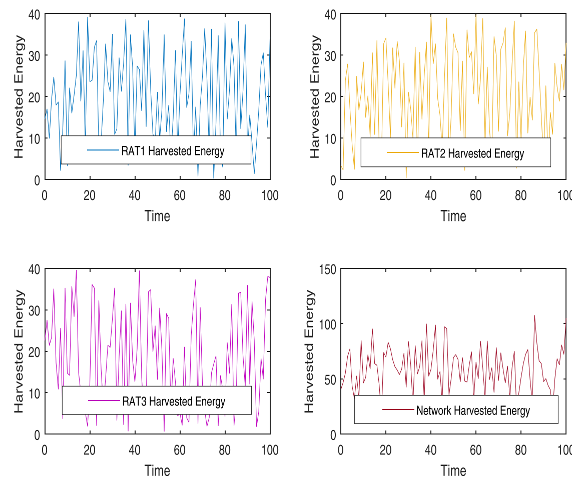


Fig. 3. Multi-RAT harvested energy arrival process.

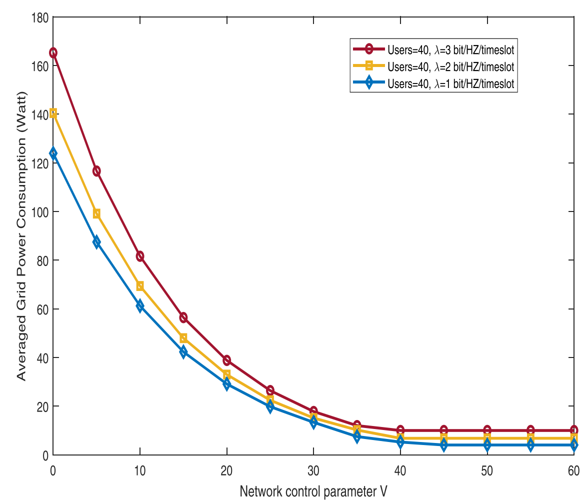


Fig. 4. Grid power consumption with parameter V.

Fig. 3 shows the harvested energy of different RATs (RAT1, RAT2 and RAT3) and the total harvested energy in terms of the time, respectively. It shows that different RATs are within the uncertainty of the arrival process of harvested energy. The total harvested energy can provide good benefits for the Multi-RAT networks, which can be implemented into practical systems with finite sized energy buffers.

Fig. 4 shows the averaged grid power consumption in terms of the network control parameter $V$ with different arrival data

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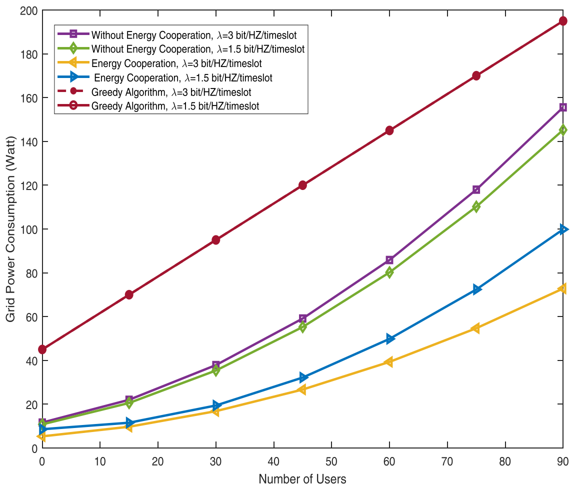


Fig. 5. Grid power consumption V.S. number of users.

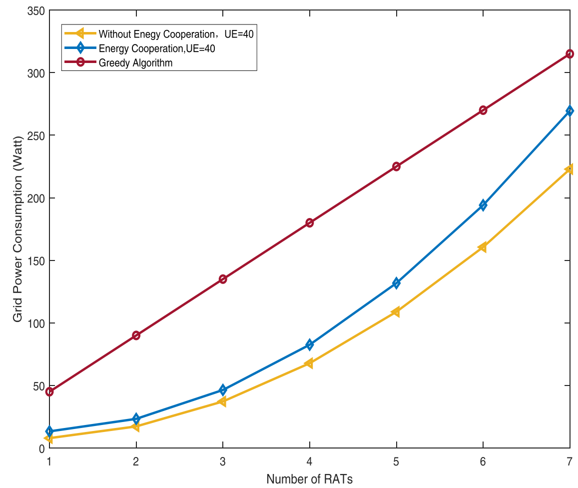


Fig. 6. Grid power consumption V.S. number of RATs.

rates. We set the different arrival data rate scenarios with the users $U = 40$. It shows that the averaged grid power consumption decreases along with the increase of $V$ at the speed of $\mathcal{O}(1/V)$. In addition, it shows that the time averaged power consumption converges to the optimal value when the network control parameter $V$ is large enough. Because the proposed algorithm is asymptotically optimal in terms of solving the original problem, which has been proved in **Theorem 1**. Furthermore, it also shows that the time averaged power consumption increases as the average arrival data rate $\lambda$ increases. Because the larger average arrival data rate $\lambda$ arrives, the larger transmission rate will occur to meet the demands of data queue stability, leading to much more consumption of time averaged power. Hence, the **Theorem 1** is validated by this experiment effectively.

Fig. 5 shows grid power consumption of the proposed algorithm in terms of the number of users, compared with the algorithm without energy cooperation. The algorithm without energy cooperation means that there is no energy transfer among multi-RAT networks with demand factor $\rho_{n,m} = 0 (n \neq m)$. It shows that the proposed algorithm consumes much less grid power than the algorithm which is without energy cooperation. Because energy cooperation can take advantage of harvested energy more efficiently due to the unbalanced nature of spatial and temporal distribution, which is taken as beneficial complement of the grid power. In addition, we compare the proposed algorithm with greedy algorithm which takes the maximum transmission power and it shows that the proposed algorithm can reduce grid power consumption effectively.

Fig. 6 shows the grid power consumption of the proposed algorithm in terms of the number of RATs compared with greedy algorithm. As expected, it shows that the grid power of the proposed algorithm consumes much less than the algorithm without energy cooperation as the increase of the number of RATs. Because the excess harvested energy of different RATs can be fully utilized with energy cooperation as the increase of the number of RATs. In addition, it shows that the proposed algorithm can reduce grid power consumption effectively compared with greedy algorithm. Hence, the proposed algorithm can gain good performance aided by the multi-RAT networks in an energy-efficient way.

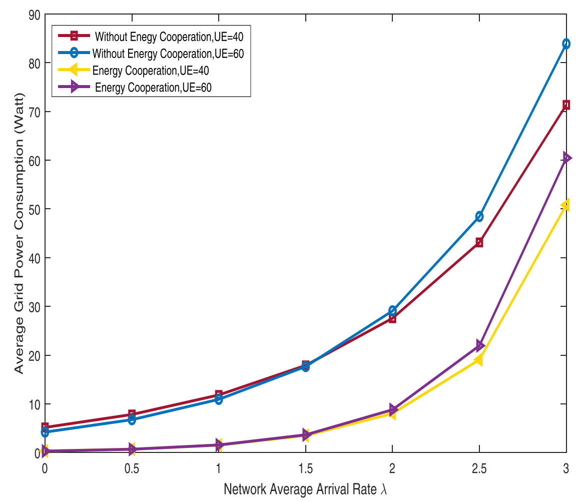


Fig. 7. Average grid power consumption V.S. average arrival rate.

Fig. 7 shows the average grid power consumption of the proposed algorithm in terms of average arrival rate. It shows that time averaged grid power consumptions under both the proposed algorithm and the algorithm without energy cooperation increase with the increasing of the arrival data rate. Furthermore, It also shows that the proposed algorithm outperforms the algorithm without energy cooperation, due to the fact that the bandwidth and power are allocated adaptively based on the dynamics of the data queue length and the wireless channel state. Hence, the proposed algorithm is quite practical in the real systems.

Fig. 8 shows the variation of the average data queue length in terms of the network control parameter $V$. It shows that the averaged data queue length increases along with the increasing of network control parameter $V$ at the rate of $\mathcal{O}(V)$, and the larger the average arrival data rate $\lambda$ is, the larger is average data queue length, due to the fact that the average arrival data rate is in proportion to the averaged data queue length based on Little's theorem.

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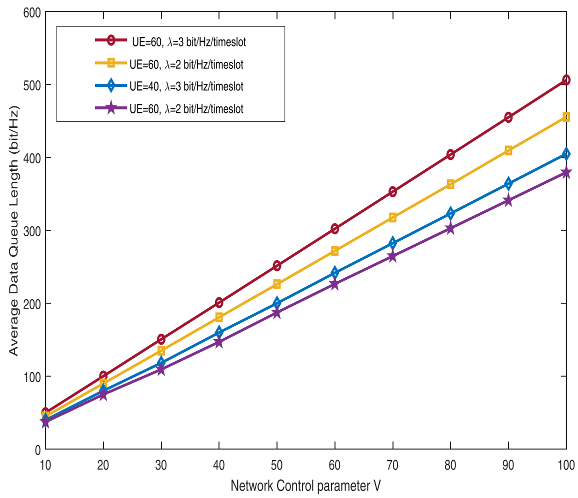


Fig. 8. Average data queue length V.S. network control parameter $V$.

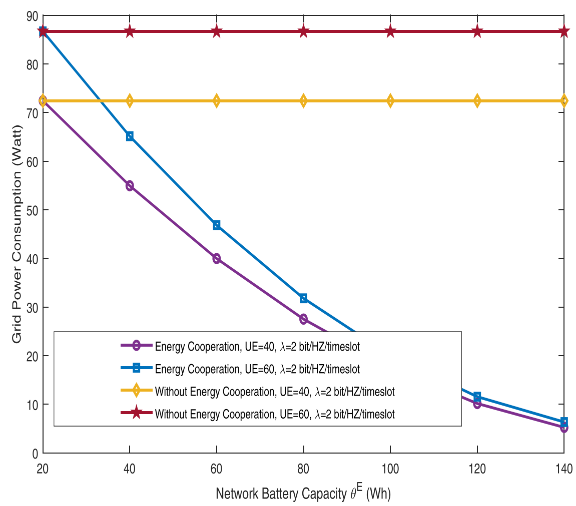


Fig. 9. Power consumption V.S. battery capacity.

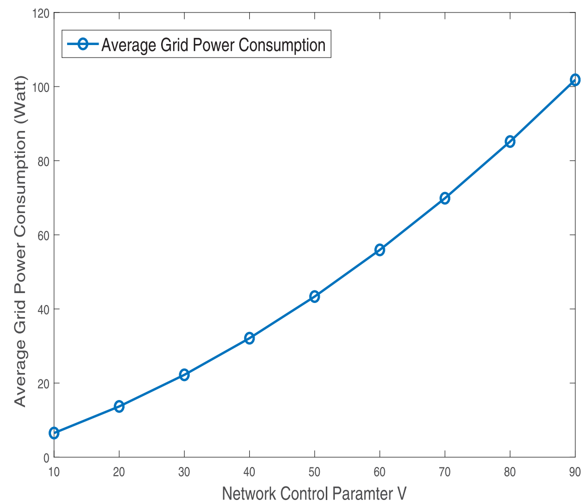


Fig. 10. Grid power v.s. V.

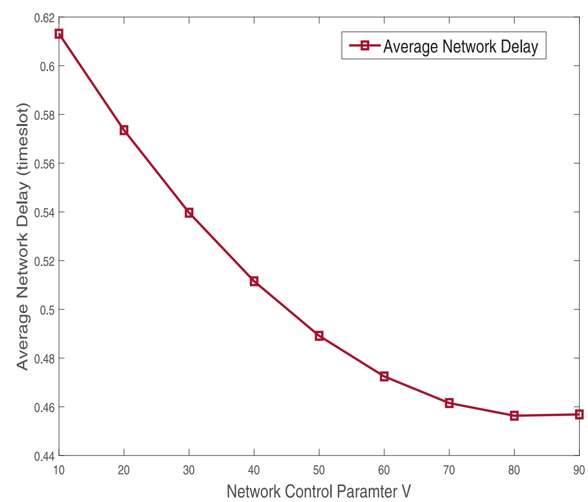


Fig. 11. Network delay v.s. V.

Fig. 9 shows the averaged grid power consumption versus the network battery capacity. It demonstrates that the multi-RAT networks with the proposed algorithm can increasingly reduce the averaged grid power consumption at the cost of increasing network battery capacity. As we know, the total transmit power consumption equals to the harvested energy added by the grid power. Thus, with much more harvested energy being stored in the increasing network battery, much less grid power will be consumed, which indeed reduces the averaged grid power cost.

Fig. 10 and Fig. 11 show the tradeoff between the averaged grid power consumption and the network delay with the variation of network control parameter $V$. It can be seen that the less averaged grid power consumes, the larger averaged delay will be. Thus, there is a tradeoff between grid power and delay, which can be quantitatively characterized with $[\mathcal{O}(1/V), \mathcal{O}(V)]$. Hence, the proposed algorithm can provide an efficient approach to allocate the resources adaptively based on the dynamic demand of multi-RAT with the network control parameter $V$. For instance, a larger $V$ will be needed if the multi-RAT prefers to save the grid power consumption, and a smaller $V$ will be set if the multi-RAT requires the lower delay performance.

## VIII. Conclusion

In this paper, we have investigated the adaptive resource allocation in multi-RATs networks which is powered by the harvested energy and the grid energy. We have proposed a realistic grid power cost model, then, we have proposed the dynamic resource-on-demand allocation algorithm to adjust to the stochastic states, i.e. randomly varying harvested energy, dynamic traffic arrival and time-varying wireless channel, requiring non-priori distribution knowledge. Furthermore, the tradeoff between grid power consumption and network delay have been captured aided by Lyapunov optimization approach. Future 5G networks equipped with energy harvesting, will operate intelligent interaction with smart grid, the smart energy trading in real-time and autonomous planning management will be investigated in our future work with artificial intelligence.

## Appendix A
## Proof of Lemma 1

*Proof:* with any non-negative scalar quantities $Q$, $\gamma$ and $b$, we can have $\max\{Q-b,0\}+\gamma)^2 \leq Q^2+b^2+\gamma^2+2Q(\gamma-b)$, then we have

$$L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t)) \leq (\boldsymbol{\gamma}(t) - \mathbf{r}(t))^H \mathbf{Q}(t)$$

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$$+\frac{1}{2}\mathbf{b}(t)^H\mathbf{r}(t)+\frac{1}{2}\boldsymbol{\gamma}(t)^H\boldsymbol{\gamma}(t),$$
$$\leq \hat{\Theta}+(\boldsymbol{\gamma}(t)-\mathbf{b}(t))^H\mathbf{Q}(t),$$

where $\hat{\Theta}$ is an upper bound of term $\frac{1}{2}[\mathbf{b}(t)^H\mathbf{b}(t)+\boldsymbol{\gamma}(t)^H\boldsymbol{\gamma}(t)]$. Adding $V\mathbb{E}[F(t)|\mathbf{Q}(t)]$ as

$$\Delta(\mathbf{Q}(t))+V\mathbb{E}[F(t)|\mathbf{Q}(t)]\leq \hat{\Theta}+V\mathbb{E}[F(t)|\mathbf{Q}(t)]$$
$$+\mathbb{E}[(\boldsymbol{\gamma}(t)-\mathbf{r}(t))^H\mathbf{Q}(t)|\mathbf{Q}(t)].$$

Hence,the proof of **Lemma 1** is completed [30]. ■

## REFERENCES


[1] N. Cheng *et al.*, "Big data driven vehicular networks," *IEEE Netw.*, vol. 32, no. 6, pp. 160–167, Nov. 2018.

[2] L. Lyu, C. Chen, S. Zhu, and X. Guan, "5G enabled codesign of energy-efficient transmission and estimation for industrial IoT systems," *IEEE Trans. Ind. Informat.*, vol. 14, no. 6, pp. 2690–2704, Jun. 2018.

[3] S. Zhang, N. Zhang, S. Zhou, J. Gong, Z. Niu, and X. Shen, "Energy-sustainable traffic steering for 5G mobile networks," *IEEE Commun. Mag.*, vol. 55, no. 11, pp. 54–60, Nov. 2017.

[4] S. Ulukus *et al.*, "Energy harvesting wireless communications: A review of recent advances," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 360–381, Mar. 2015.

[5] D. Zhang, Z. Chen, M. K. Awad, N. Zhang, H. Zhou, and X. S. Shen, "Utility-optimal resource management and allocation algorithm for energy harvesting cognitive radio sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3552–3565, Dec. 2016.

[6] I.-P. Belikaidis *et al.*, "Multi-RAT dynamic spectrum access for 5G heterogeneous networks: The SPEED-5G approach," *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 14–22, Oct. 2017.

[7] N. Zhang *et al.*, "Software defined networking enabled wireless network virtualization: Challenges and solutions," *IEEE Netw.*, vol. 31, no. 5, pp. 42–49, Mar. 2017.

[8] J. Ren, J. Hu, D. Zhang, H. Guo, Y. Zhang, and X. Shen, "RF energy harvesting and transfer in cognitive radio sensor networks: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 56, no. 1, pp. 104–110, Jan. 2018.

[9] G. Lim, C. Xiong, L. J. Cimini, and G. Ye Li, "Energy-efficient resource allocation for OFDMA-based multi-RAT networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2696–2705, May 2014.

[10] G. H. S. Carvalho, I. Woungang, A. Anpalagan, and E. Hossain, "QoS-aware energy-efficient joint radio resource management in multi-RAT heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 6343–6365, Aug. 2016.

[11] T. D. Hoang and L. Bao Le, "Joint prioritized scheduling and resource allocation for OFDMA-based wireless networks," *IEEE Trans. Wireless Commun.*, vol. 17, no. 1, pp. 310–323, Jan. 2018.

[12] G. Yu, Y. Jiang, L. Xu, and G. Y. Li, "Multi-objective energy-efficient resource allocation for multi-RAT heterogeneous networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 10, pp. 2118–2127, Oct. 2015.

[13] Q.-D. Vu, L.-N. Tran, M. Juntti, and E.-K. Hong, "Energy-efficient bandwidth and power allocation for multi-homing networks," *IEEE Trans. Signal Process.*, vol. 63, no. 7, pp. 1684–1699, Apr. 2015.

[14] Y. Mao, J. Zhang, and K. B. Letaief, "A Lyapunov optimization approach for green cellular networks with hybrid energy supplies," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2463–2477, Dec. 2015.

[15] D. Zhang *et al.*, "Resource allocation for green cloud radio access networks with hybrid energy supplies," *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 1684–1697, Feb. 2018.

[16] X. Wu, J. Yang, Y. Ran, and H. Xi, "Adaptive scalable video transmission strategy in energy harvesting communication system," *IEEE Trans. Multimedia*, vol. 17, no. 12, pp. 2345–2353, Dec. 2015.

[17] H.-J. Hung, T.-Y. Ho, S.-Y. Lee, C.-Y. Yang, and D.-N. Yang, "Relay selection for heterogeneous cellular networks with renewable green energy sources," *IEEE Trans. Mobile Comput.*, vol. 17, no. 3, pp. 661–674, Mar. 2018.

[18] S. Lohani, E. Hossain, and V. K. Bhargava, "Joint resource allocation and dynamic activation of energy harvesting small cells in OFDMA Het-Nets," *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 1768–1783, Mar. 2018.

[19] W. Xu, Y. Zhang, Q. Shi, and X. Wang, "Energy management and cross layer optimization for wireless sensor network powered by heterogeneous energy sources," *IEEE Trans. Wireless Commun.*, vol. 14, no. 5, pp. 2814–2826, May 2015.

[20] F. G. Debele, M. Meo, D. Renga, M. Ricca, and Y. Zhang, "Designing Resource-on-Demand strategies for dense WLANs," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2494–2509, Dec. 2015.

[21] Y. Wu, L. P. Qian, H. Mao, X. Yang, H. Zhou, and X. Shen, "Optimal power allocation and scheduling for non-orthogonal multiple access relay-assisted networks," *IEEE Trans. Mobile Comput.*, vol. 17, no. 11, pp. 2591–2606, Nov. 2018.

[22] C.-H. Liu and H.-C. Tsai, "On the limits of coexisting coverage and capacity in multi-RAT heterogeneous networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 5, pp. 3086–3101, May 2017.

[23] P. He, S. Zhang, L. Zhao, and X. Shen, "Multichannel power allocation for maximizing energy efficiency in wireless networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 5895–5908, Jul. 2018.

[24] S. Zhu, C. Chen, J. Xu, X. Guan, L. Xie, and K. H. Johansson, "Mitigating quantization effects on distributed sensor fusion: A least squares approach," *IEEE Trans. Signal Process.*, vol. 66, no. 13, pp. 3459–3474, Jul. 2018.

[25] M. J. Neely, "Stochastic network optimization with application to communication and queueing systems," *Synth. Lectures Commun. Netw.*, vol. 3, no. 1, pp. 1–211, Jan. 2010.

[26] S. Parsaeefard, R. Dawadi, M. Derakhshani, and T. Le-Ngoc, "Joint user-association and resource-allocation in virtualized wireless networks," *IEEE Access*, vol. 4, pp. 2738–2750, 2016.

[27] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[28] H. W. Kuhn and A. W. Tucker, "Nonlinear programming," in *Traces and Emergence of Nonlinear Programming*. Basel, Switzerland: Birkhäuser, 2014, pp. 247–258.

[29] W. Wu, Q. Yang, P. Gong, and K. S. Kwak, "Energy-efficient traffic splitting for time-varying multi-RAT wireless networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 6523–6535, Jul. 2017.

[30] W. Wu, Q. Yang, B. Li, and K. S. Kwak, "Adaptive cross-layer resource optimization in heterogeneous wireless networks with multi-homing user equipments," *IEEE J. Commun. Netw.*, vol. 18, no. 5, pp. 784–795, Oct. 2016.

[31] M. Qin, Q. Yang, J. Yang, K. S. Kwak, and R. R. Rao, "Throughput of QoS guaranteed wireless systems With/Without channel state information," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 5839–5852, Jul. 2017.


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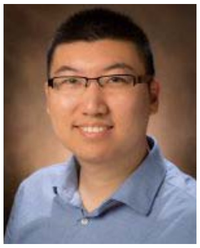

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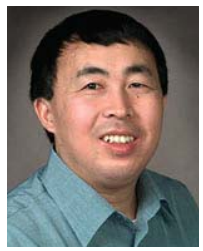

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