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Throughput Maximization for Wireless Powered Multimedia Communication Systems Under Statistical Latency Constraint

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ABSTRACT This paper investigates the relationship among the traffic throughput, statistical data latency requirement and system configurations in a wireless powered multimedia communication system. Firstly, a system model is built up with considerations of two operation modes and practical non-linear energy harvesting process. Based on the system model, the effective capacity of the considered system is derived based on the wireless charging parameter and fix data transmission rate. Then, the latency violation provability is studied by jointly taking effective capacity, traffic arrival and maximum tolerable data latency into account. Thereafter, the traffic maximization problem is transformed to the effective capacity maximization problem. Furthermore, We propose an optimal solution and a near-optimal solution to find out the system configurations of wireless charging time and transmission rate. Simulation results verify the accuracy of the near-optimal solution and also shed light on the operation mode selection in the considered system.

INDEX TERMS Wireless powered multimedia communication system, statistical latency requirement, traffic throughput, non-linear energy harvesting, system configuration.

I. INTRODUCTION

As the proposition of 5G standalone specification, we are about to enter the new era of Internet of Everything (IoE) [1]–[4]. specifically, the evolution of 5G technologies, such as new radio (NR) coding [5], [6], device to device communications (D2D) [7], [8], mobile edge caching and computing [9], [10] and etc., will bring higher data rate, lower latency and more connectives to the future communication network. As a result, various types of multimedia services have recently emerged and greatly enriches humans' production and life [11]. For instance, in Industrial Internet of Things network, tactile network and wireless sensor networks, videos or graphs are needed to monitor the operation state of the whole networks. Typically, such tasks are carried out by amounts of wireless sensors equipped with finite energy storage. It is difficult or even impossible to replace battery for those sensors when their energy is exhaust. However, the monitoring traffic usually has quality of service (QoS) requirement that must be supported with a high data transmission rate. Hence, the tradeoff between traffic QoS and the battery life attracts widely attention from both academia and industry [12].

In recent years, energy harvesting has been consider a promising technology to tackle the above mentioned tradeoff [13]. Generally, an energy harvesting communication system harvests ambient energy from solar radiation, wind, and radio frequency (RF) signal [14]–[16]. In particular, the RF energy is easier to control and utilize in terms of wireless control theory compared to the renewable solar and wind energy. As a result, the RF energy harvesting system which is usually called as wireless powered communication system have been widely studied [17], [18]. Although wireless powered communication system has great potential in monitoring traffic transmission, it is still an open query that how much traffic throughput can be guaranteed or how to configure the system under specific QoS requirements.

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Hence, the critical design issue for wireless powered multimedia system is to deal with the relationship between RF energy harvesting and data transmission under the given QoS constraint. It is infeasible to guarantee the deterministic QoS requirement as usually done in traditional wire/fiber internet due to the randomness in wireless channel fading and traffic arrivals. From engineering aspect, the QoS of a wireless communication system can be sustained from a probabilistic/statiscal view of point [19]. Concretely, it is more practical to study the latency violation probability in a wireless system, for example, the 5G uRLLC requires the probability of data latency exceeding 1ms lower than 10^{-5}. Compared to traditional wireless system, a wireless powered multimedia system has to jointly take the randomness of wireless energy transfer and data transmission into account. Moreover, the energy harvesting circuit is typically non-linear [16], [18], which aggravates the difficulty for a practical system design.

In order to achieve optimal system design to maximize the traffic throughput in a wireless powered multimedia communication system. This paper first built up a comprehensive system model including two classic operation modes in traditional wireless powered communication system, i.e., the discrete mode and hybrid mode. Particularly, the policy of fix data transmission rate and static wireless charging time is employ to simplify the design complexity and guarantee the probabilistic data latency simultaneously. Based on the proposed design idea, the effective capacity of the considered system is derived with respect to the data transmission rate and wireless charging parameter. Additionally, the relationship between the effective capacity and probabilistic data latency requirement is revealed analytically. Furthermore, the maximum throughput problem is transformed to the effective capacity maximization problem that can be solved by the two-dimension method. In detail, the optimal configuration of data transmission rate and that of wireless charging time are obtained. In addition, we also propose a near-optimal approach to solve the throughput optimization in low calculation complexity. Simulation results verify that the proposed near-optimal algorithm has at less 90% of accuracy in traffic throughput maximization.

The rest of paper is organized as follow. Section II introduces the related works about the wireless powered communication networks. In section III, the system model is constructed and the maximum traffic throughput problem is formulated. Section IV shows how to derive the effective capacity of the considered system and how to obtain the optimal system configuration. Subsequently, simulation results are presented and discussed in section V. Finally, section VI concludes this paper.

II. RELATED WORK

Usually, related studies about traffic throughput maximization in wireless powered communication networks are based on either the hybrid mode or discrete mode. In the hybrid mode, the energy transfer point and access point are integrated together while they are independently deployed in the discrete mode. The introduction of the operation mode in a wireless powered communication system can be found in Section III and Fig 1.

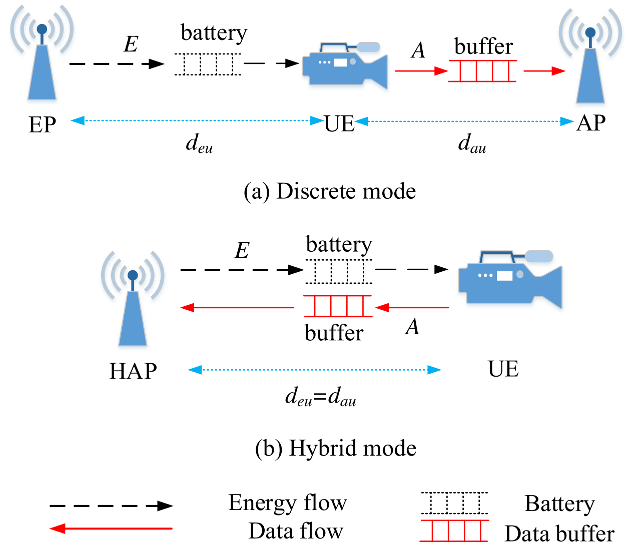

FIGURE 1. Wireless powered multimedia system with two modes: Discrete mode and hybrid mode.

The representative studies based on hybrid mode includes [20]–[23]. In [21], the sum throughput and max-min throughput of a typical wireless powered communication network were studied based on the proposed harvest-then-transmit policy. Optimal time resource allocations algorithm were obtained to maximize such two types of throughput. In [21], MIMO was used to eliminate the randomness of the wireless energy transfer such that the maximum network throughput could be improved. Works [22] focused on a dual-hop wireless powered communication network and studied the network throughput for the uplink and downlink respectively. Specifically, the time allocation for energy harvesting and data transmission was optimized to maximize the uplink throughput. Besides, the maximum downlink throughput was ascertained through optimizing the time allocation and power splitting ratio. In [23], an accumulate-then-transmit framework was built up in a full-duplex (FD) wireless-powered Internet-of-Things system. Also, a fairness-oriented scheduling scheme was studied to guarantee enough opportunity to forward data for all the users.

The representative studies based on discrete mode includes [24]–[26]. In [24], the network throughput was maximized for a wireless powered sensor network. In special, the authors therein considered a scenario that the sensors belonged to differen operators and proposed a social welfare scheme to maximize the profit of energy trading for all the operators. Works [25] studied the wireless powered cell network for two scenarios where in Scenario I, all users harvested energy from both BS and relay node, and in Scenario II, cell-edge users harvested energy from relay node only and near users harvested energy from BS only. It was found that the performance of Scenario II was better in traffic throughput guarantee with globe optimal resource allocation scheme. Taking time-varying wireless energy transfer power into account, [26] designed an efficient online algorithm to achieve high traffic throughput based on the offline case.

Typically, the harvested RF energy must be transformed to the direct current energy through a specific circuit before using it to send data. In works [20]–[26], the energy transform process is usually simply assumed to be linear and characterized by a fix efficiency parameter. However, amounts of the researches have validated that the practical energy transform is actually a non-linear process [16], [27]–[29]. Work [16] carried out a comprehensive survey in energy transfer efficiency researches where different non-linear model were review. In [27], the impact of non-linear energy harvesting process on a MIMO wireless powered communication network with discrete mode was studied. The time allocation and power control were jointly optimized to maximize the minimum individual throughput. In [28], the authors first built up a RF harvesting model by taking limited sensitivity and saturation effects into account. A piecewise linear approximation was then employed to characterize the harvested power level as a function of the channel fading. Additionally, work [29] applied the a sigmoid energy harvesting model to deal with the max-min throughput problem where optimal scheme for time allocation and RF beamforming was proposed.

The above works [20]–[29] mainly paid attention to the traffic throughput maximization without considering data latency. As mentioned before, the multimedia traffic always requires to be transmitted under some latency constraints. Hence, the analysis and system configuration schemes in [20]–[29] are not appropriate to the wireless powered multimedia communication system. To the best of our knowledge, statistical QoS studies for wireless powered communication system can only be found in [30], [31]. In [30], a resource allocation policy was studied based on a QoS exponent under the discrete mode. In [31], similar QoS exponent was employ the model the channel transmission process to satisfy the QoS requirement under the hybrid mode. However, [30], [31] failed to bridge the QoS exponent to the practical system parameter. Moreover, the energy harvesting process in [30], [31] was assumed to be linear.

In all, how to maximize the traffic throughput for a wireless powered multimedia communication system with practical non-linear energy harvesting under a specific statistical data latency requirement is still open in the literature. Besides, there is still lack of comprehensive understand that how to select the operation mode in a wireless powered communication system. These motivate the paper.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

In this paper, we consider a typical wireless powered multimedia communication system that can be used in the ubiquitous sensing scenario, e.g. Internet of Things, Industrial Internet and etc. As illustrated in Fig. 1, the considered system consists of an energy point (EP) component, an access point (AP) component and user equipment (UE). The system time is discretized into multiple consecutive time frames with identical length T. The UE is equipped with a battery to store energy and a data buffer to store data that cannot be transmitted immediately. All of the functions of the UE (mainly including sensing function and transmission function) are assumed to be sustained through harvesting wireless energy transferred by the EP. Besides, we assume that the UE works in practical half-duplex and employs the classical harvest-then-transmit protocol as depicted in Fig. 2 [20]. In each time frame, the EP firstly takes τ proportion of time to transfers wireless power to the UE in the downlink. During the remaining time of $(1-\tau)T$, with the harvested energy, the UE then not only photographs the environment periodically, but also transmits the sensing information to the AP in the uplink.

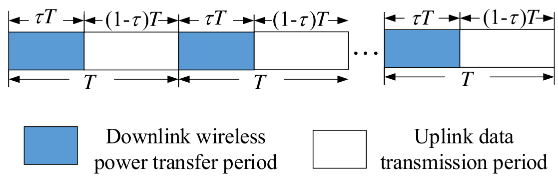

FIGURE 2. Harvest-then-transmit protocol.

TABLE 1. Variable nomenclature.

T	length of a time frame
τ	time proportion of wireless power transfer
t	the tth time frame
$h_{eu}(t)$	energy transfer power gain caused by small scale fading
$h_{au}(t)$	data transmission power gain caused by small scale fading
$pd_{h_{eu}}(x)$	pdf of $h_eu(t)$
$pd_{h_{au}}(x)$	pdf of $h_au(t)$
α_{eu}	mean value of $h_eu(t)$
α_{au}	mean value of $h_au(t)$
d_{eu}	distance between the EP and UE
d_{au}	distance between the AP and UE
$l(d_{eu})$	path loss of the link between the EP and UE
$l(d_{au})$	path loss of the link between the AP and UE
p_E	energy transfer power
$p_{RF}(t)$	harvested radio frequency power
$p_{DC}(t)$	harvested DC power
p_0	fix energy consumption rate
$E(t)$	amount of harvested DC energy
b_c	battery capacity
$p_U(t)$	transmission power of the UE
$C_U(t)$	channel capacity
t_q	maximum tolerable data latency
σ	latency violation probability
A	traffic arrival (sensing) rate
$S(t)$	cumulative channel capacity
$EC(\theta)$	effective capacity
θ	QoS exponent
$Q(t)$	data queue length
b	buffer threshold
r	data transmission (coding) rate
β	data transmission successful probability
ω_τ	accuracy requirement of τ
ω_r	accuracy requirement of r
$r^{\max}$	maximum data transmission (coding) rate

As aforementioned, there are two modes in the wireless powered multimedia communication system: the Discrete mode and the hybrid mode [20]–[26]. The difference between such two modes mainly addresses in the location of the EP and AP. As shown in Fig. 1(a) and Fig. 1(b), the EP and AP are independently deployed in the discrete mode while they are integrated in the hybrid mode. In this paper, a general analysis framework is built to compare the performance of such two modes.

Due to the reason that antenna is not the main focus in this paper, we assume that the EP, AP and UE are all equipped with single antenna. We highlight that the analysis in this paper is easily extended to the multi-antenna scenario. In wireless communications, the channel fading mainly includes the small scale fading and path loss. We use $h_{eu}(t)$ and $h_{au}(t)$ to denote the power gain of the link from the EP to UE and that of from the UE to the AP caused by small scale fading at the tth time frame, respectively. As widely assumed in the existing studies, the channel is block fading [20]–[31]. Concretely, $h_{eu}(t)$ and $h_{au}(t)$ remain invariable within a time frame while they are independently and identically distributed (i.i.d) among different time frames. In addition, we assume both the downlink and uplink channels are Rayleigh fading, which implies that $h_{eu}(t)$ and $h_{au}(t)$ follow exponential distributed [32]. The probability density functions (pdfs) of $h_{eu}(t)$ and $h_{au}(t)$ are denoted by $pd_{h_{eu}}(x)$ and $pd_{h_{au}}(x)$ respectively, which hold as

$$\begin{aligned} pd_{h_{eu}}(x) &= \frac{1}{\alpha_{eu}} e^{-\frac{1}{\alpha_{eu}}x} \\ pd_{h_{au}}(x) &= \frac{1}{\alpha_{au}} e^{-\frac{1}{\alpha_{au}}x}, \end{aligned} \tag{1}$$

where α_{eu} and α_{au} are the corresponding mean values. Similarly, $l(d_{eu})$ and $l(d_{au})$ denote the corresponding power gains caused by the path loss, where d_{eu} and d_{au} represent the distance between the EP and UE and that between the UE and the AP, respectively. Note that in the hybrid mode, we have $d_{eu} = d_{au}$ and $h_{eu}(t) = h_{au}(t)$ due to the channel reciprocity.

B. WIRELESS POWER TRANSFER MODEL

Let p_E denote the downlink transmission power from the EP, the radio frequency power received by the UE in the t time frame can be obtained as

$$p_{RF}(t) = p_E h_{eu}(t) l(d_{eu}) + N_0 W, \tag{2}$$

where N_0 and W denote the power spectral density of background noise and system bandwidth respectively. Due to the time-varying channel caused by the small scale fading and the path loss, the transmission power of the UE should be much higher than the power of the background noise. Thereby, the radio frequency energy harvested by the UE is quite high compared to the energy from the back ground noise [18]. So there holds

$$p_{RF}(t) \approx p_E h_{eu}(t) l(d_{eu}). \tag{3}$$

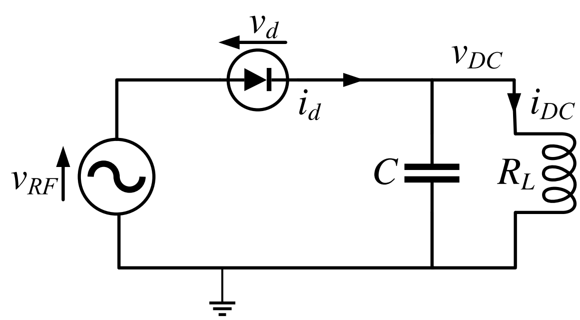

FIGURE 3. Practical energy transform circuit.

For a practical device, the harvested radio frequency energy cannot be stored or used directly until it is transformed to the direct-current (DC) energy. In most studies, such transform process is simply assumed to be linear process with an efficiency parameter [20]–[26]. However, works [16], [27]–[29] verify that the transform process from radio frequency energy to DC energy is always non-linear and propose an empirical energy transform model. The practical energy transform circuit is depicted as Fig. 3, based on which the DC energy harvesting rate holds as [16]

$$p_{DC}(t) = \frac{\Phi_{DC}(t) - p_s \Delta}{1-\Delta}, \tag{4}$$

where

$$\begin{aligned} \Delta &= \frac{1}{1+e^{\xi_1 \xi_2}} \\ \Phi_{DC}(t) &= \frac{p_s}{1+e^{-\xi_1 (p_{RF}(t) - \xi_2)}}. \end{aligned}$$

Here, $\Phi_{DC}(t)$ is the logistic function with respect to the harvested radio frequency power $p_{RF}(t)$. Δ is a constant that ensure the zero-input/zero-output for the wireless power transfer. p_s denotes the maximum DC energy harvesting rate when the energy transform circuit tends to be in saturate state. Besides, ξ_1 and ξ_2 characterize the joint effect of the resistance, capacitance, and circuit sensitivity, which leads to the non-linear property of the energy transform circuit. Note that, p_s, ξ_1 and ξ_2 can be easily ascertained with the help of curve fitting tools. The DC energy harvesting rate can then be further derived as

$$p_{DC}(t) = p_s \frac{1 - e^{-\xi_1 p_{RF}(t)}}{1+e^{-\xi_1 (p_{RF}(t) - \xi_2)}}. \tag{5}$$

As a result, the amount of harvested DC energy in the tth time frame holds as follows

$$E(t) = \min\{\max\{(p_{DC}(t) - p_0, 0)\tau T, b_c\}, \tag{6}$$

where b_c denotes the battery capacity of the UE. Besides p_0 denotes the equivalent energy consumption rate used in data sensing and other functionalities of the UE in each time frame. Eq. (6) means that the amount of the harvested DC energy is constrained by the battery capacity and fix energy consumption.

C. DATA TRANSMISSION MODEL

Let $p_U(t)$ denote the unlink data transmission power of the UE in the tth time frame. According to the Shannon theorem, the uplink channel capacity in the tth time frame holds as

$$C_U(t) = W \log_2(1 + \frac{p_U(t)h_{au}(t)l(d_{au})}{N_0 W}). \tag{7}$$

According to Eq. (7), higher transmission power $p_U(t)$ brings higher channel capacity. Consequently, in order to maximize the traffic throughput of the UE in every time frame, $p_U(t)$ should be set to use up the available harvested energy in each time frame. Hence, $p_U(t)$ is set as follows

$$p_U(t) = \frac{E(t)}{(1-\tau)T}, \tag{8}$$

D. PROBLEM FORMULATION

Because of the time-varying property of the wireless channel, the wireless energy transfer rate and uplink channel capacity are random over time. On the other hand, the multimedia traffic always requires to be transmitted under a given latency constraint [33]. In this paper, we study the system configuration policy to guarantee the data transmission performance from the probabilistic point of view. In specific, the data transmission performance requirement is denoted by a tuple (t_q, σ), which holds as

$$Pr\{D(t) > t_q\} \leq \sigma, \tag{9}$$

where $D(t)$ means the data latency in the tth time frame. Here, Eq. (10) means that in each time frame, the data latency exceeds a maximum tolerable value t_q should be within probability σ. Note that the data transmission performance is highly related to the traffic arrival (sensing) rate, the wireless power transfer and channel capacity. Moreover, we would like the UE to transmit sensing information to the AP as much as possible with given resources. Let A denote the traffic arrival rate. The optimization problem is then formulated as

$$\begin{aligned} \textbf{P1:} \ & \max_{\tau, r} \quad A \\ & \text{subject to} \ \ Pr\{D(t) > t_q\} \leq \sigma. \end{aligned} \tag{10}$$

Although problem **P1:** only has one constraint, it is a non-linear problem due to the non-linear energy transform process. Moreover, the challenge of solving this problem addresses in how to associate the data latency constraint with the traffic arrival, wireless energy transfer and data transmission.

IV. PERFORMANCE ANALYSIS

In this section, the effective capacity theory is applied to solve problem **P1:**. The effective capacity theory is first introduced. The data latency performance is then studied with consideration of traffic arrivals, stochastic wireless energy transfer and time-varying channel capacity. Thereafter, we will show how to maximize the traffic throughput when performance requirements and system resources are given.

A. EFFECTIVE CAPACITY

The effective capacity theory proposed by D. Wu in 2003 is applied to analyze the statistical quality of service (QoS) guarantee for wireless communication system where channel gain is time-varying [34]. It is defined as the maximum constant arrival rate that a given service process can sustain under a given statistical QoS requirement. Let $S(t)$ denote the cumulative service process of the system from the 1st time frame to the tth time frame, which holds as $S(t) = \sum_{i=1}^{t} R(i)(1-\tau)T$, where $R(i)$ denotes the service rate in the ith time frame. The effective capacity of $S(t)$ is defined as [34]

$$EC(\theta) = -\frac{1}{\theta t T} \log(\mathbb{E}[e^{-\theta S(t)}]), \tag{11}$$

where $\mathbb{E}[\cdot]$ represents expectation function and θ is a QoS exponent. According to the large derivation principle, reference [35] proves that the queue length $Q(t)$ of a stationary and ergodic system converge in distribution to a random variable $Q(\infty)$, i.e.,

$$-\lim_{b \to \infty} \frac{\log(Pr\{Q(\infty) > b\})}{b} = \theta, \tag{12}$$

where b can be considered as data buffer threshold. More superficially, Eq. (12) indicates that probability of the queue length exceeding b decays exponentially with rate θ as b increases.

From Eq. (11), it is not clear what is the relationship between the effective capacity and the system parameters. Moreover, since the multimedia traffic is usually delay-sensitive and the UE is resource constraint, it is difficult for a UE to obtain the perfect channel state information in each time frame, especially in the discrete mode where the downlink and uplink channels are different. Thus, it is more practical for the UE to transmit data in a fix coding rate over time rather than employing adaptive coding policy. The following theorem summarizes the effective capacity for the considered wireless powered multimedia communication system.

Theorem 1: Given a fix data transmission rate r, the effective capacity of the considered system with discrete mode can be obtained as

$$EC(\theta) = -\frac{\log(e^{-\theta r(1-\tau)T}\beta + 1 - \beta)}{\theta T}, \tag{13}$$

where

$$\beta = \int_{f^{-1}(p_0)}^{f^{-1}(\frac{b_c}{\tau T})} e^{-\frac{1}{\alpha_{au}}\frac{\phi}{f(z)-p_0}} \frac{1}{\alpha_{eu}} e^{-\frac{1}{\alpha_{eu}}z} dz + e^{-\frac{1}{\alpha_{au}}\frac{\phi}{\frac{b_c}{\tau T}-p_0}} e^{-\frac{1}{\alpha_{eu}} f^{-1}(b_c)}, \tag{14}$$

denotes the probability that the data can be successfully transmitted with a given r. Additionally, ϕ and $f(z)$ are defined in Eq. (16) and Eq. (17) respectively. And $f^{-1}(\cdot)$ is the inverse function of $f(\cdot)$.

Proof: As the instantaneous channel state information is not available, the data can only be successfully transmitted iff the transmission rate is not greater than the instantaneous channel capacity. As a result, the service rate in the ith time frame holds as

$$R(i)=\begin{cases} r & r\le C_U(i)\\ 0 & \text{otherwise.}\end{cases} \tag{15}$$

According to Eq. (7), $C_U(t)$ is an increasing function with respect to $h_{au}(t)$ and $p_U(t)$. Hence, we have

$$\begin{aligned} r\ \le\ C_U(i) &\Leftrightarrow p_U(t)h_{au}(t)\ge\frac{(2^{\frac{r}{W}}-1)N_0W}{l(d_{au})}\\ &\Leftrightarrow E(t)h_{au}(t)\ge\frac{(2^{\frac{r}{W}}-1)N_0W(1-\tau)T}{l(d_{au})}\\ &\Leftrightarrow (p_{DC}-p_0)h_{au}(t)\ge\frac{(2^{\frac{r}{W}}-1)N_0W(1-\tau)}{l(d_{au})\tau}\triangleq\phi, \end{aligned} \tag{16}$$

when $E(t)\le b_c$. Besides, it is easily verified that $p_{DC}(t$ increases with $p_{RF}(t)$ and $p_{RF}(t)$ increases with $h_{eu}(t)$ according to Eq. (3) and Eq. (4). Therefore,

$$\begin{aligned} p_{DC}(t)&=p_s\frac{1-e^{-\xi_1 p_E h_{eu}(t)l(d_{eu})}}{1+e^{-\xi_1(p_E h_{eu}(t)l(d_{eu})-\xi_2)}}\\ &\triangleq f(h_{eu}(t)) \end{aligned} \tag{17}$$

is a monotonously increasing function in $h_{eu}(t)$. The data transmission success probability, denoted by β, is then obtained as

$$\begin{aligned} \beta\ &=\ Pr\{C_U(i)\ge r\}\\ &=\ Pr\{(p_{DC}(t)-p_0)h_{au}(t)\ge\phi\}\\ &=\ \int_{p_0}^{p_s} pd_{p_{DC}}(x)dx\int_{\frac{\phi}{x-p_0}}^{+\infty} pd_{h_{au}}(y)dy\\ &=\ \int_{p_0}^{p_s} e^{-\frac{1}{\alpha_{au}}\frac{\phi}{x-p_0}}pd_{p_{DC}}(x)dx\\ &\overset{x\to f(z)}{=}\ \int_{f^{-1}(p_0)}^{f^{-1}(\frac{b_c}{\tau T})} e^{-\frac{1}{\alpha_{au}}\frac{\phi}{f(z)-p_0}}pd_{h_{eu}}(z)dz\\ &\qquad+\int_{f^{-1}(\frac{b_c}{\tau T})}^{+\infty} e^{-\frac{1}{\alpha_{au}}\frac{\phi}{\frac{b_c}{\tau T}-p_0}}pd_{h_{eu}}(z)dz\\ &=\ \int_{f^{-1}(p_0)}^{f^{-1}(\frac{b_c}{\tau T})} e^{-\frac{1}{\alpha_{au}}\frac{\phi}{f(z)-p_0}}\frac{1}{\alpha_{eu}}e^{-\frac{1}{\alpha_{eu}}z}dz\\ &\qquad+e^{-\frac{1}{\alpha_{au}}\frac{\phi}{\frac{b_c}{\tau T}-p_0}}e^{-\frac{1}{\alpha_{eu}}f^{-1}(b_c)}. \end{aligned} \tag{18}$$

Here, $f^{-1}(\cdot)$ meas the inverse function of $f(\cdot)$. Based on the definition of effective capacity (11), we then have

$$\begin{aligned} EC(\theta)\ &=\ -\frac{1}{\theta tT}\log(\mathbb{E}[e^{-\theta S(t)}])\\ &=\ -\frac{1}{\theta tT}\log(\mathbb{E}[e^{-\theta\sum_{i=1}^{t}R(i)(1-\tau)T}])\\ &\overset{(a)}{=}\ -\frac{1}{\theta tT}\log(\prod_{i=1}^{t}\mathbb{E}[e^{-\theta R(i)(1-\tau)T}])\\ &=\ -\frac{1}{\theta T}\log(\mathbb{E}[e^{-\theta R(i)(1-\tau)T}])\\ &=\ -\frac{1}{\theta T}\log(e^{-\theta r(1-\tau)T}\beta+1-\beta) \end{aligned}$$

Here. step (a) holds because $R(i)$ is i.i.d variable. The reason is that $C_U(i)$ depends on $h_{eu}(i)$ and $h_{au}(i)$ that both follow i.i.d distributed. Thus, Theorem 1 is proved. □

Note that the analysis for the system with hybrid mode is similar where the only difference addresses in there always holds $h_{eu}(i)=h_{au}(i)$. We omit the derivation in this paper and only show results for discussion.

B. LATENCY PERFORMANCE

When b is sufficiently large, Eq. (12) can be transformed as

$$Pr\{Q(t)>b\}\approx e^{-\theta b}. \tag{19}$$

Further related the queue length to the data latency, we have $Q(t)=D(t)EC(\theta)$ and $b=t_qEC(\theta)$ [36]. Combining Eq. (10) and Eq. (19), the latency performance (t_q,σ) can be obtained as

$$\begin{aligned} Pr\{D(t)>t_q\}\ &\le\ e^{-\theta EC(\theta)t_q}\\ &\overset{(a)}{=}\ e^{\frac{\log(e^{-\theta r(1-\tau)T}\beta+1-\beta)}{T}t_q}\\ &=\ (e^{-\theta r(1-\tau)T}\beta+1-\beta)^{\frac{t_q}{T}}\\ &=\ \sigma. \end{aligned} \tag{20}$$

Here, step (a) is based on Theorem 1. From Eq. (20), the data latency performance is highly related to the exponent parameter θ. Besides, θ is related to the traffic arrival rate A and the effective capacity $EC(\theta)$. A larger θ means better latency performance or tight latency requirement. The effective capacity decreases as θ increases, which means it is more and more difficult to guarantee the data latency if the requirement become tighter and tighter. Therefore, it cannot be infinitely large. Given traffic arrival rate A, the maximum (optimal) θ hold as [37]

$$\theta^{\max}=\{\theta:A=EC(\theta)\}. \tag{21}$$

C. TRAFFIC THROUGHPUT MAXIMIZATION

This subsection will show how to choose the charging parameter τ and data transmission rate r to maximize the average traffic throughput under the given latency constraint (t_q,σ). In order to guarantee the system stability and delay constraint at the same time, the traffic arrival rate should not be greater the effective capacity, i.e., there always holds

$$A\le EC(\theta). \tag{22}$$

Hence, problem **P1** can be transformed into the following problem

$$\begin{aligned} \textbf{P2:}\ \max_{\tau,r}\quad & EC(\theta)\\ \text{subject to}\quad & Pr\{D(t)>t_q\}\le\sigma. \end{aligned} \tag{23}$$

Based on the relationship between the QoS exponent θ and the latency constraint (t_q,σ) obtained in Eq. (20), there holds

$$\theta=-\frac{\ln(1-\frac{1-\sigma^{\frac{T}{t_q}}}{\beta})}{r(1-\tau)T}. \tag{24}$$

Inserting Eq. (24) into Theorem 1, problem **P2** can be further transformed as

$$\textbf{P3:}\quad \max_{\tau,r}\ EC = \frac{\ln(\sigma^{\frac{T}{t_q}})r(1-\tau)}{\ln(1-\frac{1-\sigma^{\frac{T}{t_q}}}{\beta})}. \tag{25}$$

It is observed that problem **P3** is still no-linear problem. On one hand, a higher τ means the UE has longer time to harvest wireless energy but shorter time to transmit data, and otherwise. On the other hand, a higher r means the UE can transmit more data in a time frame but suffer lower data transmission successful probability, and other wise. According to Eq. (16), Eq. (17) and Eq. (18), the data transmission successful probability β depends on both τ and r. However, as derived in Eq. (18), the close-form of β does not exist, which can only be determined with the help of calculation software. This implies that the optimal τ and r cannot be obtained in close-form. Fortunately, in practical system, the granularity of coding rate and that time slot are usually determined, which provide a feasibility to apply the two-dimension search algorithm to find out the optimal configuration, as summarized in Algorithm 1. Let ω_τ and ω_r denote the step length for τ and r respectively and $r^{\max}$ denote the maximum coding rate. The calculation complexity of Algorithm 1 holds as $O(\frac{Tr^{\max}}{\omega_\tau\omega_r})$.

Algorithm 1 Optimal Solution of Problem **P3**

initialize $\tau = 0$ with step length ω_τ, $r = 0$ with step length ω_r, maximum coding rate $r^{\max}$ and other system parameters from Eq. (17);
$\tau^{\text{opt}} = \tau$, $r^{\text{opt}} = r$, $EC^{\max} = 0$;
repeat
  repeat
    Calculate β according to (18).
    Calculate θ according to (24).
    Calculate EC according to (25).
    if $EC > EC^{\text{opt}} = 0$ **then**
      $\tau^{\text{opt}} = \tau$, $r^{\text{opt}} = r$, $EC^{\max} = EC$;
    end if
    $\tau = \tau + \frac{\omega_\tau}{T}$;
  until $\tau > 1$
  $\tau = 0$, $r = r + \omega_r$;
until $r > r^{\max}$
output τ^{opt}, r^{opt}, $EC^{\max}$;

Note that the calculation complexity to find out τ^{opt} increases linearly as the time frame length T increases for given r. For the scenario with large T, computation complexity to solve problem **P3** is still high. In what follows, we study a near-optimal solution for τ^{opt}. From Eq. (25), the effective capacity EC increases with β and $r(1-\tau)$. Besides, according to Eq. (18), there holds

$$\begin{aligned}\beta &= Pr\{C_U(i) \geq r\}\\ &= Pr\{C_U(i)(1-\tau) \geq r(1-\tau)\},\end{aligned} \tag{26}$$

which means increasing $C_U(i)(1-\tau)$ statistically can increase β when $r(1-\tau)$ is fixed or increase $r(1-\tau)$ when β is fixed. Therefore, we aim to maximize $C_U(i)(1-\tau)$ to increase EC based on the system parameters. Note that $C_U(i)(1-\tau)$ is time-varying, in order to guarantee the transmission performance for a long-term transmission with an effective static τ, the time-varying system parameter (i.e., h_{eu} and h_{au}) can be replaced by their mean values denoted by h_{eu}^m and h_{au}^m. Recall (7), we have

$$g(\tau) \triangleq C_U(1-\tau) = \frac{W}{\ln 2}\log(1+K\frac{\tau}{1-\tau})(1-\tau), \tag{27}$$

where

$$\begin{aligned}K &= \frac{(p_{DC}-p_0)h_{au}^m l(d_{au})}{N_0W}\\ &= \frac{(p_s\frac{1-e^{-\xi_1 p_E h_{eu}^m l(d_{eu})}}{1+e^{-\xi_1(p_E h_{eu}^m l(d_{eu})-\xi_2)}} - p_0)h_{au}^m l(d_{au})}{N_0W}.\end{aligned} \tag{28}$$

Note that the objective is to maximize $g(\tau)$, thereby there always holds $p_{DC} - p_0 > 0$. Let $\tau_1 = 1-\tau \in (0,1)$, there holds

$$\begin{aligned}g(\tau_1) &= \frac{W}{\ln 2}\log(1+K\frac{1-\tau_1}{\tau_1})\tau_1\\ &= \frac{W}{\ln 2}\log(1-K+\frac{K}{\tau_1})\tau_1\end{aligned} \tag{29}$$

The second-order derivatives of $g(\tau_1)$ in τ_1 can be calculated as

$$\frac{\partial^2 g(\tau_1)}{\partial \tau_1^2} = -\frac{K^2}{\tau_1^3(1-K+\frac{K}{\tau_1})^2} < 0 \tag{30}$$

Hence $g(\tau_1)$ is convex function in τ_1, i.e., there is a solution τ_1^{opt} to maximize $g(\tau_1)$ when $\tau_1 \in (0,1)$. Let the first-order derivatives of $g(\tau_1)$ in τ_1 equal to 0, i.e.,

$$\begin{aligned}&\frac{\partial g(\tau_1)}{\partial \tau_1} = \ln(1-K+\frac{K}{\tau_1}) - \frac{K}{(1-K+\frac{K}{\tau_1})\tau_1} = 0\\ &\Updownarrow\\ &(1-K+\frac{K}{\tau_1})\ln(1-K+\frac{K}{\tau_1}) - (1-K+\frac{K}{\tau_1})\\ &\quad +1-K = 0\end{aligned} \tag{31}$$

Further let $c = (1-K+\frac{K}{\tau_1}) \geq 0$ and define

$$n(c) = c\ln(c) - c + 1 - K \tag{32}$$

We have

$$\begin{aligned}\frac{\partial n(c)}{\partial c} &= \ln(c)\\ \frac{\partial^2 n(c)}{\partial c^2} &= \frac{1}{z}\end{aligned} \tag{33}$$

Thus, $n(c)$ is a convex function in $c \geq 0$ and when $c = 1$, $n(c)$ got its minimum $n(1) = -K$. Note that $\lim_{c\to 0} n(c) = 1-K < 0$, there are not any solution of $n(c) = 0$ in $c \in (0,1)$. On the other hand, $n(c) = 0$ is monotonically increasing when $c > 1$. As a result, there must exist a unique solution $c^* > 1$ to meet $n(c) = 0$. According to Eq. (27), Eq. (29), Eq. (30)

and Eq. (31), the optimal τ to maximize $C_U(1-\tau)$, i.e., to obtain the near-optimal effective capacity holds as

$$\tau^{\mathrm{nopt}} = 1 - \tau_1^{\mathrm{nopt}} = \frac{c^* - 1}{c^* - 1 + K}, \tag{34}$$

where K can be obtained from (28), c^* is the solution of $n(c) = 0$ in (32) and can be obtained by the dichotomy method. Finally, Algorithm 2 summarizes how to obtain the near-optimal configuration of τ and r. Different from Algorithm 1, Algorithm 2 finds out τ^{opt} through dichotomy method in step 4 whose calculation complexity is $O(\log_2(\frac{T}{\omega_\tau}))$. Therefore, the calculation complexity of Algorithm 2 holds as $O(\log_2(\frac{T}{\omega_\tau})\frac{r^{\max}}{\omega_r})$.

Algorithm 2 Near-Optimal Solution of Problem **P3**

1: **initialize** $r = 0$ with step length ω_r, maximum coding rate $r^{\max}$ and other system parameters from Eq. (17);
2: $r^{\mathrm{opt}} = r$, $EC^{\max} = 0$;
3: Calculate K according to (28);
4: Solve $n(c) = 0$ in (32) and obtain c^*;
5: Calculate τ^{nopt} according to (34);
6: **repeat**
7: Calculate β according to (18).
8: Calculate θ according to (24).
9: Calculate EC according to (25).
10: **if** $EC > EC^{\mathrm{opt}} = 0$ **then**
11: $\omega^{\mathrm{nopt}} = \omega$, $EC^{\mathrm{nmax}} = EC$;
12: **end if**
13: $r = r + \omega_r$;
14: **until** $r > r^{\max}$
15: **output** τ^{nopt}, r^{nopt}, EC^{nmax};

V. SIMULATION RESULTS

In the subsequent, simulation results are presented and discussed in the considered wireless powered multimedia system under both discrete mode and hybrid mode. Without special announcement, default system configurations are as follows. The wireless transfer power of the EP is set as $p_E = 10$W. The battery of the UE b_c is assumed to be 10J. The power spectral density of background noise N_0 and the overall system bandwidth W are set to 130dBm and 1MHz. The mean power gain of the downlink and that of the uplink due to the small are both set to be 1, i.e., $h_{au}^m = h_{eu}^m = 1$. The distance between the EP and the UE and that between the AP and UE are both set as $d_{eu} = d_{au} = 5$m. The path loss function is set to $l_i(d_i) = -30\text{dB} - 20\log_1 0(d_i)$, where $i = \{eu, au\}$. For the energy transform circuit, we employ the fitting parameters from [16], i.e., the saturated power $p_s = 0.1071$mW, the non-linear parameters $\xi_1 = 6.9349 \times 10^3$ and $\xi_2 = 0.6614 \times 10^{-4}$. The fix equivalent energy consumption rate is set to $p_0 = 1\mu$W. In addition, the time frame length T is set to be 100ms and the data latency requirement is set to $(t_q, \sigma) = (500\text{ms}, 0.01)$.

Fig. 4 shows how the traffic throughput (or effective capacity) can be guaranteed with different configurations of data transmission rate r and wireless charging time proportion τ.

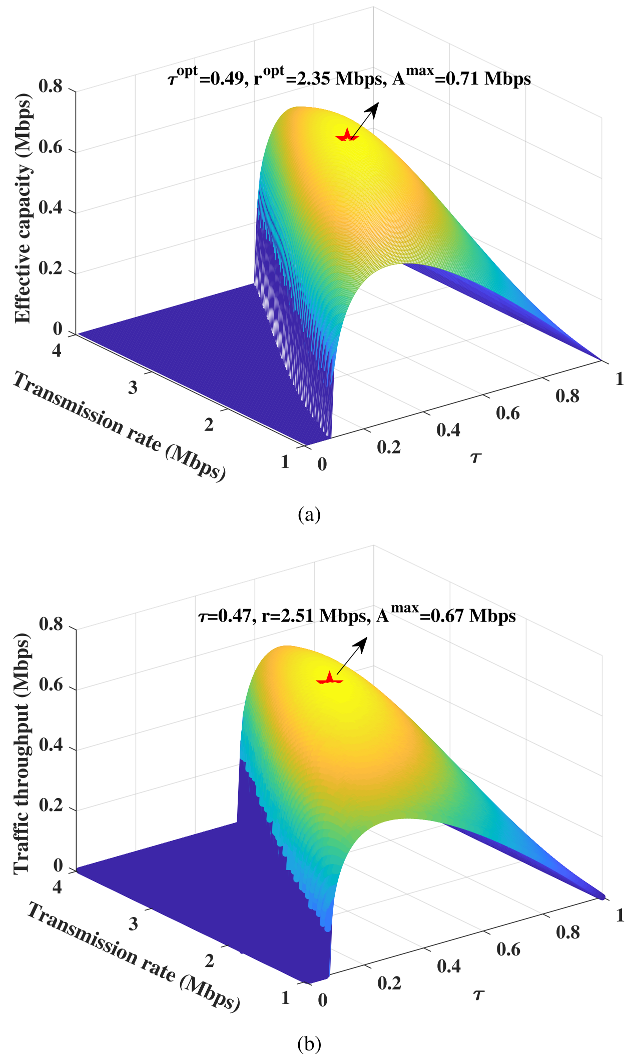

FIGURE 4. Traffic throughput varying with wireless power charging parameter and transmission rate: (a) Discrete mode, (b) hybrid mode.

It is observed that optimal joint configuration exists under either discrete mode or hybrid mode. With identical default system parameter configurations except r and τ, the maximum traffic throughput sustained by the discrete mode is higher than the maximum traffic throughput sustained by the hybrid mode. This is because the channel state of the downlink and that of the uplink are the same in the hybrid mode due to the channel reciprocity while they are independent in the discrete mode. Compared to the discrete mode, the impact of channel fading on the system performance under hybrid mode is double. In other words, the discrete mode has lower probability to fall in poor channel state than the hybrid mode. It is also observed the traffic cannot be sustained under a latency requirement when r is not sufficiently low and τ is not sufficiently large. It can be explained that a small τ leads to little harvested harvesting and low channel capacity while a high transmission rate leads to lower transmission successful probability. From Eq. (20), lower β results in looser data latency guarantee.

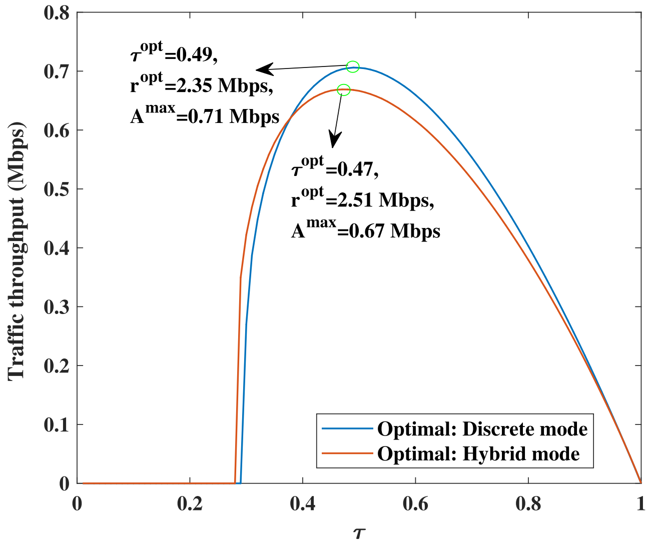

FIGURE 5. Impact of wireless charging time on the traffic throughput.

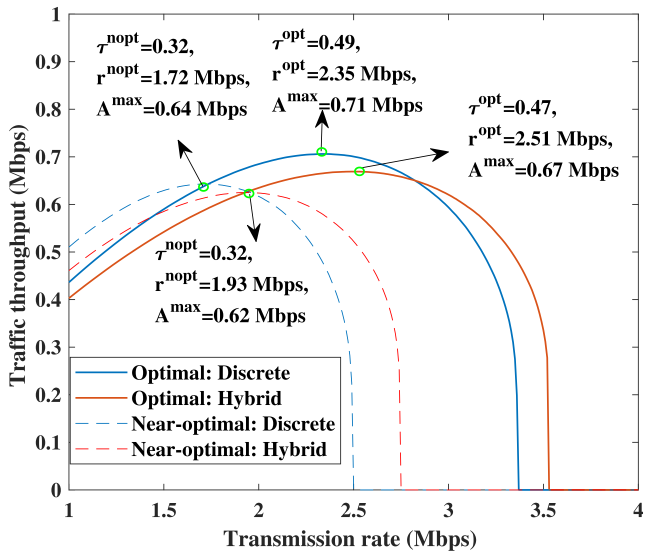

FIGURE 6. Performance comparison between the optimal algorithm and near-optimal algorithm.

Additionally, we find the optimal joint configurations are different between these two modes, where the discrete mode can guarantee higher transmission rate but needs more time to harvest wireless energy. Those phenomenons are depicted in detail in Fig. 5 and Fig. 6. The reason is that the channel state under the discrete mode is statistically better, which thereby results in higher channel capacity. Therefore, higher transmission rate is permitted in terms of a given transmission successful probability. This impels the UE to take more time to harvest energy.

Fig. 6 also shows the performance comparison between the proposed optimal algorithm and the near-optimal algorithm under the discrete and hybrid modes. Though the configurations of r and τ seem to be quite different between the two proposed algorithms, we highlight that the gap of throughput obtained based on those two algorithms are 0.07 Mbps under

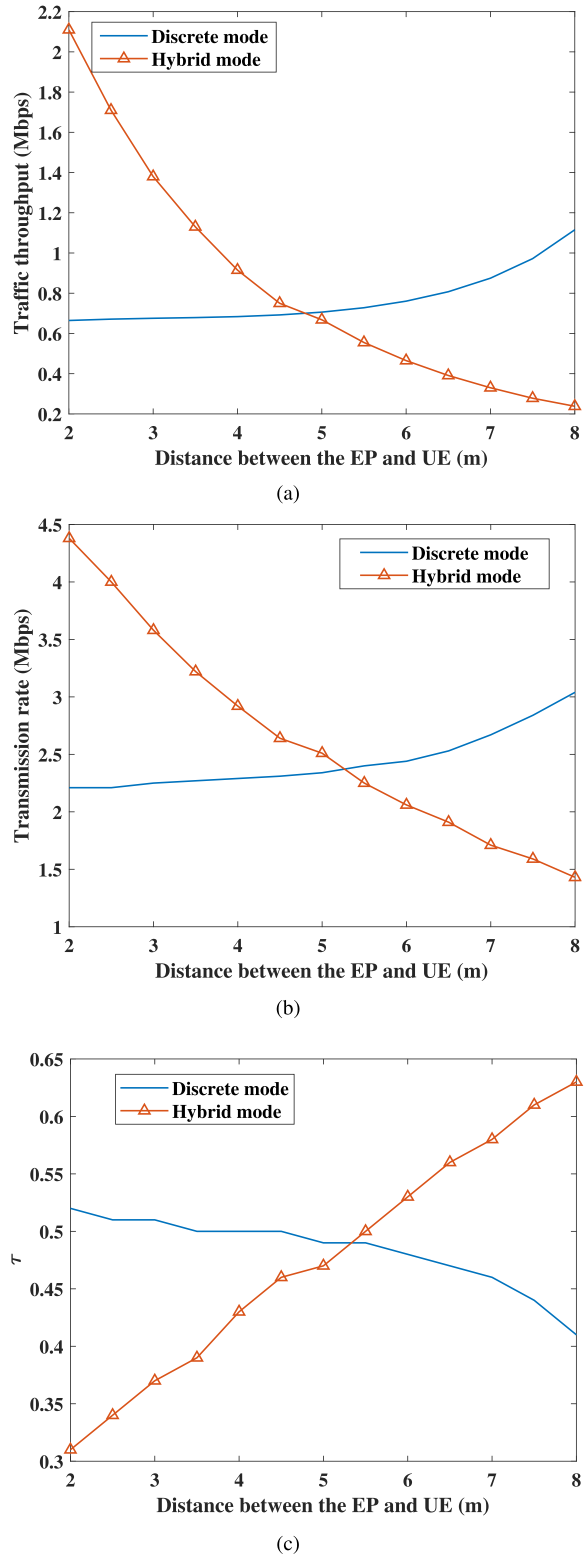

FIGURE 7. Impact of wireless charging distance on the system performance and configurations: (a) Traffic throughput, (b) transmission rate, (c) charging time proportion.

the discrete mode and 0.05 Mbps under the hybrid mode, respectively. It is easily verified that the gap is lower than 10% of the optimal traffic throughput, implying that the near-optimal algorithm still guarantees more than 90% of the traffic throughput with much lower configuration complexity.

In Fig. 7, the impact of wireless charging distance on the system performance and configurations is presented. We assume that the EP, UE and AP are located in line in order. The distance between the EP and AP is set to 10m and thereby we have $d_{au} = 10 - d_{eu}$ in the discrete mode. Differently, d_{au} is always equal to d_{eu} in the hybrid mode. We find that the varying trends of $A^{\max}$, r and τ under the discrete mode are all opposite to those under the hybrid mode. In special, $A^{\max}$, r and τ are less sensitive to wireless charging distance under the discrete mode. This is due to the complementarity of the path loss between wireless energy transfer and data transmission. Specifically, a larger d_{eu} leads to a severer path loss on wireless energy transfer but result in smaller path on data transmission. If the UE is closer to the EP, it can take less time to harvest energy and more time to transmit data. Conversely, If the UE is closer to the AP, more time can be taken to perform wireless charging and less time is enough to guarantee a sufficiently high channel capacity. In hybrid mode, however, the impact of d_{eu} is double compared to traditional communication without wireless energy harvesting. This is because the UE has to suffer the same path loss on both wireless charging and data transmission, which is called as the double near-far phenomenon [20]. Consequently, the selection of the operation mode in wireless powered multimedia communication system should take the location of the UE into account. More specifically, from Fig. 7(a), if the distance between the EP and UE is on the left of the cross point, we should choose the hybrid mode, otherwise discrete mode is better.

VI. CONCLUSION

In this paper, time allocation for wireless energy transfer and rate configuration for data transmission were jointly studied with the object to maximize the traffic throughput in a wireless powered multimedia communication system under statistical data latency requirement. The effective capacity and data latency distribution were obtained. Besides, optimal and near-optimal schemes were proposed to improve the traffic throughput. Moreover, the performance of the discrete and hybrid operation modes were comprehensively analyzed and compared. Finally, a selection guide line was also proposed based on the simulation results.

We highlight that analysis in this paper is appropriate to the lower-power communication scenarios including the wireless sensor networks, IoT and mobile crowdsensing [38]. However, the proposed scheme should be adjusted in terms of the specific characteristics of different scenarios. Therefore, our future work will address in combing wireless energy transfer with information sensing. We will also be interested in the system design for those practical systems.

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