IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 10, 2019, accepted March 3, 2019, date of publication March 12, 2019, date of current version April 1, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2904664

Strategic Access and Pricing in Internet of Things (IoT) Service With Energy Harvesting

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This work was supported in part by the National Natural Science Foundation of China under Grant 71871008, Grant 71571014, and Grant 61601336, and in part by the 111 Project of China under Grant B16002, in part by the A*STAR-NTU-SUTD Joint Research Grant Call on Artificial Intelligence for the Future of Manufacturing under Grant RGANS1906 and Grant WASP/NTU M4082187 (4080), in part by the Singapore MOE Tier 1 under Grant 2017-T1-002-007 RG122/17, in part by the MOE Tier 2 under Grant MOE2014-T2-2-015 ARC4/15, in part by the NRF, Singapore, under Grant NRF2015-NRF-ISF001-2277, and in part by the Singapore EMA Energy Resilience under Grant NRF2017EWT-EP003-041.

ABSTRACT This paper studies an interaction between the Internet of Things (IoT) device and users, both of which act strategically to achieve their own objectives. In the IoT system under consideration, the users access the service provided by the IoT device, e.g., to obtain sensing information. The device relies on energy harvesting to serve the users who are priced when accessing the service. When the delay cost of users is considered, we propose a game-theoretic queuing model to analyze the pricing strategy of the device and strategic joining rules for users. A Stackelberg game is formulated, in which the device, i.e., the leader, determines the service price to maximize his revenue facing the strategic users, i.e., the followers who determine their equilibrium joining strategy to maximize their own utility. Interestingly, we find that the equilibrium joining probability can be non-monotone in the length of energy harvesting time. Moreover, from the perspective of a social planner, the optimal service price to induce the maximal social welfare is derived, and the Price of Anarchy metric is examined accordingly. The numerical examples disclose that the socially optimal price should be lower than the optimal price for the device.

INDEX TERMS Internet of things (IoT), energy harvesting, Stackelberg game, equilibrium, price of anarchy.

I. INTRODUCTION

Internet of Things (IoT) has become a promising solution to connect various physical objects and enable data sensing and exchange among them, such as sensors, vehicles, and personal digital devices [2]. The development of IoT has brought great benefits to many practical applications, e.g., healthcare and transportation. With a well-designed IoT system, the connected objects, devices, and applications, can communicate and operate autonomously without or with minimal human intervention to provide efficient and useful services [3]. Since the IoT devices have to operate remotely or in a mobile environment, the device has limited energy supply. Energy harvesting techniques can be used at the device as a means to supply energy [4]–[6], [8], [10]–[12]. Different modes of energy harvesting are available for the device including solar, vibration, wind, and wireless signals such as magnet resonance and radio frequency (RF) [13].

One of the important issues in IoT systems or in wireless sensor networks is the energy harvesting. In an IoT system, the IoT device can be regarded as a sensor node receiving an access request from IoT applications and users. If the device has enough energy, it will serve the request by sending the sensing information back to the user. Otherwise, these requests will be blocked. For all its prevalence, using energy harvesting in the IoT device faces some significant challenges. Firstly, the availability of energy supply from ambient sources is random. Thus, energy outage can happen unpredictably. Secondly, when multiple users request for a service from the IoT device, the device can be busy serving one request and also the energy depletes quickly. This causes a competitive situation among the users in accessing the

The associate editor coordinating the review of this manuscript and approving it for publication was Adnan M. Abu-Mahfouz.

service and/or waiting for the device to be available. This phenomenon is also known as ''negative externality''.

On the other hand, an IoT device can be regarded as a service provider or seller, it can charge the users for serving their requests to generate revenue and profit. As such, the self-interested IoT device and users have to act strategically to reach an equilibrium solution of such an IoT system.

In this paper, we present a joint queuing and game theoretic model for the aforementioned IoT system. We focus on the service management of an IoT device with a retrial queue and general service time when the energy harvesting is considered. The model is thus able to characterize repeated behavior in communication networks. Different from conventional queuing models where an IoT user's request always finds an idle server for immediately service processing, the device in the IoT system model under our consideration relies on energy harvesting, and the service delay as well as unavailability is expected. In this regard, if the IoT device is busy, e.g., due to energy harvesting or serving the other user' request, the incoming request may be recalled to a waiting orbit and processed again later, namely, retrial behavior. Among these incoming requests, upon arrival some of them may also balk from the system based on their utilities. Additionally, we employ a two-stage Stackelberg game to model the interaction between the IoT device and users. The strategy of the IoT users is the service joining probability which indicates the decision that the user chooses to wait if its request cannot be satisfied by the IoT device immediately. On the other hand, the strategy of the IoT device is to set the price charged per user's request served. The Stackelberg equilibrium of the game is obtained which maximizes the revenue of the IoT device given that the users adopt the best response service joining probability. Apart from the Stackelberg equilibrium, we also analyze the maximal social welfare of the IoT system from the perspective of a social planner.

In summary, we have the following several contributions: (1) The system performance measures (e.g., steady-state probabilities as well as mean delay) with energy harvesting and retrial orbit are derived. (2) The equilibrium strategy for users is characterized, in which the equilibrium joining probability can be non-monotone in the average time of energy harvesting. (3) The optimal pricing strategy for IoT device and social planner are obtained and compared. To the best of our knowledge, this is the first work that studies the energy harvesting in the IoT system when the balking and retrial behaviors of users are considered, and service pricing is incorporated. In particular, it is for the first time that the concept of ''rational queuing'' is adopted and applied in the communications with energy harvesting context. To this end, we investigate the Price of Anarchy (PoA) analytically and numerically.

The reminder of paper is organized as follows. Section II reviews the related work. Section III introduces the system model considered in this paper. The equilibrium service joining strategy of IoT users is derived in Section IV. In Section V, the revenue of IoT device and its optimal service price is obtained. An optimal social welfare strategy which maximizes the utility of the users and the revenue of the IoT device is derived in Section VI. The Price of Anarchy (PoA) for social welfare is investigated in Section VII. Section VIII presents the performance evaluation. Finally, Section IX concludes the paper, all proofs and two more extensions are provided in Appendix.

II. RELATED WORK

A. ENERGY EFFICIENCY AND ENERGY HARVESTING IN INTERNET OF THINGS (IoT) SYSTEMS

In practical IoT systems, many limitations such as device size, cost, and energy supply may affect the system performance, which are related to the energy efficiency of IoT devices [14]. Energy is always among the most important resources for IoT systems to sustain their operation. In many IoT sensing applications, energy harvesting such as solar, wind, vibration, and RF, is employed at the IoT devices or sensors as replacing or charging their battery are nearly technically impossible and/or economically infeasible. Reference [15] shows that energy supply and storage of IoT nodes may affect the topology and lifetime of the whole network. Therefore, energy management is significant for IoT systems to achieve the optimal performance.

Energy management and energy efficiency designs in IoT systems have been studied extensively in existing literature. For example, Aziz *et al.* [15] defined the direct impacts of single node energy to the whole network performance. Data caching is employed in [16] for a sensor node in IoT to avoid frequently sensing to minimize the consumption of energy. For the next 5G IoT networks, energy efficiency has to be optimized efficiently and the energy usage should be reduced by 90% compared with the current designs [17]. However, energy efficiency designs in wireless sensor networks are not directly applicable to IoT scenarios, due to the features of IoT systems such as the vast diversity and cost-aware communication patterns [18], [19]. An energy efficiency framework combining both wireless and wired subsystems of IoT systems is studied in [20].

To overcome the energy supply limitation, energy harvesting techniques [4] are developed to replenish a battery of a mobile device including an IoT node. Energy sources are diverse such as motion and vibration [5], electromagnetic field [6], ambient RF energy [8], dedicated RF energy [10], solar energy [11], and combined energy sources [12]. A recent major development of energy harvesting is RF energy transfer, called simultaneous wireless information and power transfer (SWIPT). SWIPT allows an energy and information source, e.g., a wireless base station, to transfer information and energy simultaneously to a receiver [21]–[23]. Although SWIPT supports mostly the downlink transmission, the same concept is applied for the uplink which suits more to IoT systems, i.e., data transmission from IoT nodes to a gateway. The major challenge of energy harvesting is the low energy efficiency due to the additive effect of limited transmission power, transmission loss, and RF-to-DC conversion efficiency [24]. Low energy efficiency may cause exhaustion of battery energy for IoT devices with batteries or low energy supply for battery-free IoT designs, which significantly affects IoT service quality.

B. QUEUEING THEORY AND OPTIMIZATION

To model and analyze energy efficiency in IoT systems, stochastic optimization and analysis approaches have been applied. In particular, queuing theory is employed as a classical service management model to analyze systems where users' access requests are processed sequentially. Energy arrival was considered in a discrete manner as energy packets in [25]. Here, energy packets arrive following a Poisson arrival pattern. A coupled dual-queue Markovian system model was studied in [26], where each mobile node has unlimited buffer size for data flow but limited energy buffer size for energy harvesting. The study in [26] was on performance metrics of energy management in the case of unstable connectivity, where an optimal energy buffer size is derived, and the system stability in terms of energy overflow and depletion is analyzed.

For the queuing theory modeled energy harvesting systems, game theoretic analyses have been conducted by some studies in the literature. For example, in [27], an $M/M/N/N$ queue was formulated to describe the competition among N users, whose bidding strategy for energy receiving from an access point converges to a Nash equilibrium. Li *et al.* [28] modeled an energy queue at a base station which receives energy supplied by either traditional electric grid or renewable energy. A non-cooperative game was formulated and solved to investigate an interaction between the renewable energy supplier and the base station. Game theoretic analysis on queuing with retrial behaviors in a local area network (LAN) was performed in [29] and [30], where the retrial rate is linear to the number of users in the orbit.

Evidently, existing literature mainly focuses on the behaviors and performance metrics of energy harvesting. However, strategic interactions between IoT device and users through service pricing and service joining, respectively, were not studied before. Especially with unstable energy harvesting, retrial behaviors, as well as social welfare of the IoT system require further analysis and investigation which are the focuses of this paper.

III. SYSTEM MODEL

The IoT system under consideration is illustrated in Fig. 1. In the system, the IoT device, e.g., a sensor node, employs an energy harvesting technique, e.g., RF energy. The device is equipped with an energy harvester, a controller unit, and energy storage [31]. A super-capacitor which requires a lower voltage level to charge than that of a rechargeable battery is commonly used in such IoT devices. However, the super-capacitor has a limited capacity which is typically sufficient only for few packet transmissions. Therefore, once the IoT device transmits some packet to a user, it does not have enough energy in its energy storage to transmit more data. Consequently, the IoT device has to harvest energy and recharge its energy storage which takes a certain time period, during which it is unavailable.

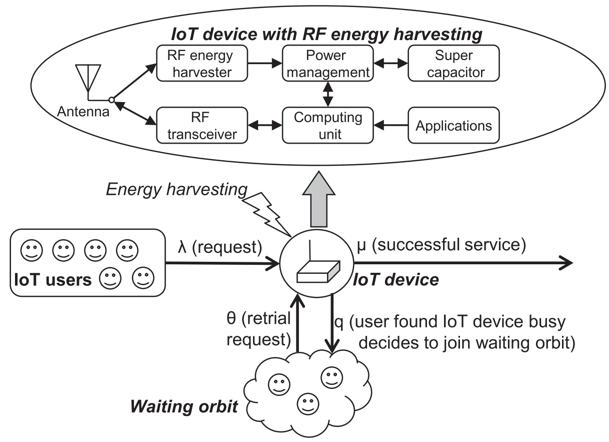

FIGURE 1. System model of IoT service.

Based on the above typical setting of an IoT device, when the IoT device receives a request from one of the users, it will serve the user immediately, e.g., transmitting sensing information to the user, if it is idle. And the IoT device is idle if and only if it has sufficient energy and it is not serving any other user. After the IoT device finishes serving the user, the device will switch to an energy harvesting mode, during which it cannot serve any incoming user. If a user sends a request when the IoT device is busy, i.e., serving any other user, or when it is harvesting energy, the user will not be served, i.e., the incoming user is blocked. The blocked user then may put itself in a waiting orbit and will retry to access the IoT device again later.[1] After the IoT device harvests enough energy, it will be idle and able to serve an incoming user which can be a new user or repeating user among the users in the waiting orbit.

The homogeneous users request to access the IoT device with a positive arrival rate λ which follows the Poisson process. In practice, in many IoT sensing services, the homogeneous users use the same applications which leads to the similar service access behavior such as arrival and retrial rates. The IoT device's service time follows a general distribution with mean $E[S] = 1/\mu$, where $\mu > 0$ can be regarded as the service rate. The variance of service time is denoted by $Var[S] = E[S^2] - E^2[S]$. After serving the user, an average time that the IoT device spends to harvest energy is $1/\beta$. However, if the user finds the IoT device unavailable (busy or harvesting energy), the user, with probability $q \in [0, 1]$, joins the waiting orbit. Each user in the waiting orbit will retry to access the device again with rate θ, i.e., the retrial rate. The retrial interval is determined by the capacity of communication system and is independent to the strategy

[1] For the rest of the paper, we use "IoT service" and "IoT device" interchangeably.

of users. Other users who choose to balk (with probability $1 - q$) will leave the system, and have no chances to retry their accesses as the ones in orbit in the future. In this case, the overall retrial rate from the orbit to the IoT device is linear to the number of users and is independent to users' behavior. That is, the users just make the joining-balking decision. An example timing describing this scenario is shown in Fig. 2.

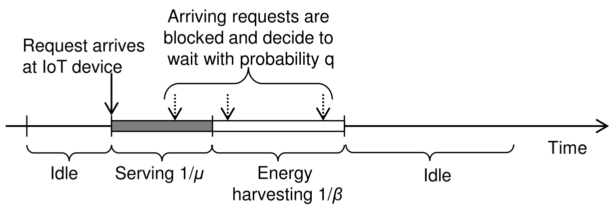

FIGURE 2. Example timing.

If the IoT device serves the user, the device charges a positive service price denoted by P to the user, e.g., through the IoT service provider which can be the owner of the device. After the user is served, the user receives a positive reward denoted by R. Furthermore, sending a request and receiving the result incur a positive cost per unit time, e.g., bandwidth usage, denoted by C to the user. Here, the IoT device sets and announces the price first. Based on the price, the user makes a decision that whether to join or balk to determine whether the user will join the waiting orbit to wait and retry to access the IoT device again or not. Denote by $T(q)$ the average delay for the joining users when all other users adopt a curtain joining probability q, then the tagged arriving user needs to determine the joining probability $\hat{q} \in [0, 1]$ so as to maximize her expected utility:

$$\arg\max_{\hat{q}\in[0,1]} U(\hat{q}; q) \triangleq \hat{q} \cdot U(q) = \hat{q}[R - P - CT(q)], \quad (1)$$

where $U(q)$ is the expected utility for user if she chooses to join. As we are investigating the behavior homogeneous users, we consider the symmetric equilibrium among them. Therefore, q_e characterizes an equilibrium if and only if $\arg\max_{\hat{q}\in[0,1]} U(\hat{q}; q_e) = q_e$. On the other hand, the IoT device can choose an optimal service price to maximize its revenue, knowing how the price affects the service joining probability of the users. Again, if one of the users is being served, the other users cannot be served. This creates a competitive situation among the users whose strategy has to be adjusted accordingly. Under this circumstance, we formulate a two-stage Stackelberg game to model the interaction between the IoT device and users. The **players** of the game are the IoT device, i.e., the leader, and the users, i.e., the followers. The **strategy** of the IoT device is the service price while that of the users is the joining probability. Here, the IoT device chooses the price before the users choose the service joining probability, and hence the users are able to observe the price strategy of the IoT device. Under equilibrium, the **payoff** of joining users is their utility (i.e., $U(q_e)$), while the IoT device is the revenue per time unit $\lambda_e P = \lambda[\pi_a + q_e \cdot \pi_u] \cdot P$, where $\lambda_e = [\pi_a + q_e \cdot \pi_u]$ is the overall effective arrival rate, π_a and π_u are the probabilities that the system is available and unavailable, respectively.

Next, we follow backward induction by analyzing the strategy of the users first. Then, the strategy of the IoT device is examined.

IV. USERS' (FOLLOWERS') STRATEGY

In the Stackelberg game, we first analyze the strategy of the users in terms of the service joining probability given service price P charged by the IoT device. In the model, the users are indistinguishable upon their arrivals which forms a symmetric game among them. An incoming user that finds the IoT device idle will be served immediately, and upon service completion, the user receives utility $R > 0$, where naturally $R > P$. On the contrary, the user that finds the IoT device busy or harvesting energy upon arrival, i.e., the blocked user, cannot be served and the corresponding user has a mixed strategy specified by the service joining probability q, where $q \in [0, 1]$. The goal here is to obtain the Nash equilibrium service joining strategy among symmetric users. We first give the performance analysis of system for the fixed joining probability q, and then the equilibrium q_e is characterized.

A. PERFORMANCE ANALYSIS

The service time distribution function is $B(x)$ for both new and repeating users. We assume that the input flow of users, intervals between repetitions, and service times are mutually independent. Let $I(t)$ denote the state of the IoT device at time t. The events $I(t) = 0, 1, 2$ correspond to, respectively, the states that the IoT device is idle, busy serving a user, or harvesting energy. Let $N(t)$ be the number of users in the waiting orbit at time t. Here, the IoT system can be regarded as a queuing system in which the server is the IoT device and the queue is for the users waiting in the orbit. Accordingly, the state space of the IoT system is denoted by

$$\Delta = \Big\{(I, N); I \in \{0, 1, 2\}, N \in \{0, 1, \ldots\}\Big\}. \quad (2)$$

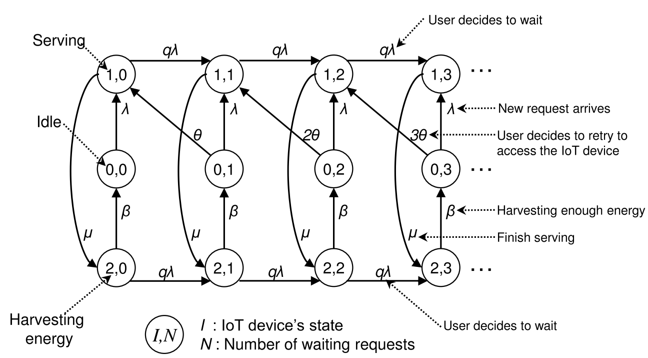

FIGURE 3. State transition diagram of the IoT system.

Fig. 3 shows the state transition diagram in the Markovian case, i.e., when the service time is exponential distribution.

The IoT device's state may start from the idle state, and it transits to the busy (serving) state when a user arrives, i.e., with the rate λ. After the IoT device finishes serving the user with the rate μ, it transits to the energy harvesting state, and subsequently transits to the idle state again with the rate β. The number of users in the waiting orbit increases if a user arrives when the IoT device is in the busy state or energy harvesting state. The increase rate is weighted by the probability q. Then, if IoT device becomes idle when there is a user in the waiting orbit, the device becomes busy again if one of the users retries. Here, the rate of retrying, i.e., $\theta, 2\theta, 3\theta, \ldots$, increases as the number of users in the waiting orbit increases. This is from the fact that each of the users can retry independently.

However, the stochastic process of the IoT service $\{(I(t), N(t)), t \geq 0\}$ is not the continuous time Markov chain when we consider a general service time. Thus, we introduce a supplementary variable $\xi(t)$ as the elapsed service time of the user being served when $I(t) = 1$. Let $b(x) = \frac{B'(x)}{1-B(x)}$ be the instantaneous service intensity given that the elapsed service time is equal to x, where $B'(x) = dB(x)/dx$ is the probability density function for service time S. We let the joint distribution of the IoT device state and queue length, i.e., the number of users in the waiting orbit, in the steady-state state are as follows:

$$p_{0n} = \text{Prob}[I(t) = 0, N(t) = n], \tag{3}$$

$$p_{1n}(x) = \frac{\text{d}}{\text{d}x}\text{Prob}[I(t) = 1, \xi(t) < x, N(t) = n], \tag{4}$$

$$p_{2n} = \text{Prob}[I(t) = 2, N(t) = n], \tag{5}$$

where $\xi(t)$ is the elapsed service time in t and $p_{1n} = \int_0^\infty p_{1n}(x)\text{d}x$.

We define the following generating functions:

$$\Pi_i(z) = \sum_{j=0}^{\infty} p_{i,j}z^j, \quad \Pi_1(z, x) = \sum_{j=0}^{\infty} p_{1,j}(x)z^j, \tag{6}$$

for $i = 0, 2$. Then, the balance equations are expressed as follows:

$$(\lambda + i\theta)p_{0i} = \beta p_{2i}, \tag{7}$$

$$\frac{\text{d}p_{1i}(x)}{\text{d}x} = -(\lambda q + b(x))p_{1i}(x) + \lambda q p_{1,i-1}(x), \tag{8}$$

$$p_{1i}(0) = \lambda p_{0i} + (i + 1)\theta p_{0,i+1}, \tag{9}$$

$$(\lambda q + \beta)p_{2i} = \lambda q p_{2,i-1} + \int_0^\infty p_{1i}(x)b(x)\text{d}x, \tag{10}$$

where $p_{i,-1} = 0, i \geq 0$.

Theorem 1: For the IoT system with energy harvesting in the steady state, the users enter the waiting orbit with probability q when they find the IoT device unavailable upon the arrival. Let $\rho = \lambda E[S]$ and $K'' = \lambda^2 q^2 E[S^2]$. We derive the following results under $\beta > \lambda q + \rho q \beta$.

1) The probabilities that the IoT device is idle, busy, or harvesting energy are, respectively, given by

$$\Pi_0(1) = \frac{\beta - \lambda q - \beta\rho q}{(1 - q)(\lambda + \rho\beta) + \beta}, \tag{11}$$

$$\Pi_1(1) = \frac{\rho\beta}{(1 - q)(\lambda + \rho\beta) + \beta}, \tag{12}$$

$$\Pi_2(1) = \frac{\lambda}{(1 - q)(\lambda + \rho\beta) + \beta}. \tag{13}$$

2) The mean numbers of users in the waiting orbit when the IoT device is idle, busy, or harvesting energy are, respectively, given by (14)–(16), as shown at the bottom of this page.

3) The expected waiting time for the repeating users is given by

$$T(q) = \frac{1}{\theta} + \frac{\lambda + \rho\beta}{\theta(\beta - \lambda q - \rho q\beta)} + \frac{\lambda + \rho\beta + \frac{K''\beta^2}{2q^2\lambda}}{(\lambda + \rho\beta)(\beta - \lambda q - \rho q\beta)}, \tag{17}$$

which is strictly increasing for q$\in$ [0, 1].

Remark: Theorem 1 shows that the expected waiting time for blocked users is increasing in their joining probability q. It is intuitive because when q increases, the system will become more congested, and more negative externalities are resulted. Thus the mean delay for them would be increased. From the denominator of $T(q)$, we can derive the sufficient and necessary condition for the system stability as follows: $\beta > \lambda q + \rho q\beta$. Since the arrival rate λ can be too large which affects the stability, we consider two cases to discuss the equilibrium strategy of service joining probability of the users. These two cases are $\lambda < \frac{\mu\beta}{\mu+\beta}$ and $\lambda \geq \frac{\mu\beta}{\mu+\beta}$. Furthermore, with the reward and cost of the user accessing

$$N_0 = \frac{\lambda q(\lambda + \rho\beta)}{\theta((1 - q)(\lambda + \rho\beta) + \beta)}, \tag{14}$$

$$N_1 = \frac{\theta(2(\lambda q)^2 q\rho + 2\lambda\beta(\rho q)^2 q - \lambda q K''\beta + K''\beta^2) + 2\lambda q^2\rho\beta(\lambda + \rho\beta)}{2\theta((1 - q)(\lambda + \rho\beta) + \beta)(\beta - \lambda q - \rho q\beta)q}, \tag{15}$$

$$N_2 = \frac{\lambda\theta(-2\beta\rho^2 q^2 + 2\rho q\beta - 2\rho q^2\lambda + \beta K'' + 2\lambda q) + 2\lambda^2 q(\lambda + \rho\beta)}{2\theta((1 - q)(\lambda + \rho\beta) + \beta)(\beta - \lambda q - \rho q\beta)}. \tag{16}$$

the IoT device, the expected utility of the joining user who finds a unavailable server is expressed as follows:

$$U(q) = R - P - CT(q) = R - P - C\left(\frac{\beta + (1-q)(\lambda+\rho\beta)}{\theta(\beta - \lambda q - \rho q\beta)} + \frac{\lambda + \rho\beta + \frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)(\beta - \lambda q - \rho q\beta)}\right), \quad (18)$$

where R is the reward of the service completion, P is the price charged by the IoT device, and C is the cost of the user. The utility in (18) is for the general service time distribution. Nonetheless, we can consider two special cases, i.e., deterministic service time and exponentially distributed service time.

For the deterministic service time, i.e., $Var[S] = 0$, the service time degenerates to a constant $1/\mu$ with probability one. The expected utility of the blocked user is obtained as follows:

$$U(q) = R - P - C\left(\frac{\beta + (1-q)(\lambda+\rho\beta)}{\theta(\beta - \lambda q - \rho q\beta)} + \frac{\lambda + \rho\beta + \frac{\rho\beta^2}{2\mu}}{(\lambda+\rho\beta)(\beta - \lambda q - \rho q\beta)}\right). \quad (19)$$

For the exponentially distributed service time, the expected utility becomes

$$U(q) = R - P - C\left(\frac{1}{\theta} + \frac{(\mu+\beta)^2(\theta+\lambda) - \theta\mu\beta}{\theta(\mu+\beta)(\mu\beta - (\mu+\beta)\lambda q)}\right). \quad (20)$$

It is not difficult to verify that the expected utility for blocked users who decide to join the system is higher under deterministic service time, because of the lower variance. So far, for a given q, the expected utility of users can be determined. Next, we will characterize the equilibrium joining probability, i.e., q_e, based on the utility.

B. EQUILIBRIUM JOINING STRATEGY

Notice that $U(q) < R - P$ for any $q \in [0, 1]$, to avoid triviality, we just consider the case of $R - P > 0$. Otherwise, none of the users would join the waiting orbit. As we have proven the monotonicity of average waiting time in the orbit, the equilibrium service joining strategy for the users can be determined uniquely for the given reward-cost values and price P. We consider the equilibrium in both cases, i.e., $\lambda < \frac{\mu\beta}{\mu+\beta}$ and $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, in the following theorem.

Theorem 2: In the IoT system with energy harvesting, a unique Nash equilibrium strategy of the users observing the IoT device unavailable upon the arrival, i.e., blocked users, to join the waiting orbit, i.e., probability q_e, exists. The probability q_e is given as follows.

For $\lambda < \frac{\mu\beta}{\mu+\beta}$, we have

$$q_e = \begin{cases} 0, & \text{if } 0 < \frac{R-P}{C} < T(0), \\ \frac{[(R-P)\theta - C]\beta - (\lambda + \rho\beta + \theta + \frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})C}{[(R-P)\theta - C](\lambda+\rho\beta)}, & \text{if } T(0) \leq \frac{R-P}{C} \leq T(1), \\ 1, & \text{if } \frac{R-P}{C} > T(1), \end{cases} \quad (21)$$

and for $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, we have

$$q_e = \begin{cases} 0, & \text{if } 0 < \frac{R-P}{C} < T(0), \\ \frac{[(R-P)\theta - C]\beta - (\lambda + \rho\beta + \theta + \frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})C}{[(R-P)\theta - C](\lambda+\rho\beta)}, & \text{if } T(0) \leq \frac{R-P}{C}, \end{cases} \quad (22)$$

where

$$T(0) = \frac{1}{\theta} + \frac{\lambda+\rho\beta}{\theta\beta} + \frac{\lambda + \rho\beta + \frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)\beta}, \quad (23)$$

$$T(1) = \frac{1}{\theta} + \frac{\lambda+\rho\beta}{\theta((1-\rho)\beta - \lambda)} + \frac{\lambda + \rho\beta + \frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)((1-\rho)\beta - \lambda)}. \quad (24)$$

Remark: Theorem 2 shows that there exists unique equilibrium strategy in the IoT system with energy harvesting. When $q_e = 0$, i.e., R is small, it can be explained by that the users have no alternative than getting the device's information, i.e., they simply cannot wait or decide to leave the system when the IoT device is found to be unavailable. Because $U(q)$ is a decreasing in $q \in [0, 1]$, when all other blocked users adopt a higher joining probability q, the tagged user is more hesitate to join the system because if she does, a lower utility is obtained. Therefore, the best response of the tagged user is decreasing in the joining strategy of others. That is, we have an "avoid the crowd (ATC)" (see [9] and [29] for further descriptions about ATC) situation for the queuing system. It can be explained by the negative externalities that are made by other users.

In the following, we show some important properties of the equilibrium service joining strategy.

Theorem 3: In the IoT system with energy harvesting, the Nash equilibrium strategy of joining probability q_e has the following properties under $\beta > \lambda q + \rho q\beta$.

1) The equilibrium joining probability q_e is increasing in the retrial rate θ.
2) q_e is not monotone in the energy harvesting rate β. Specifically, for the service time variance $Var[S] < \overline{V}$, q_e is increasing in β. Otherwise, q_e is unimodal in β, where $\overline{V} = \frac{(R-P)\theta - C}{C\theta\mu}$.

Remark: Theorem 3 shows that in the IoT system, when the energy harvesting rate increases, it does not necessarily induce a higher equilibrium joining probability for the users. In particular, when the energy harvesting time is shorter, the blocked users may be less inclined to join the waiting orbit. This result is counter-intuitive because a shorter harvesting time normally means a smaller total delay for the users. Nonetheless, this phenomenon can be interpreted as follows. When β increases, more users will find that it is more easily to be served by the IoT device. Therefore, they do not need to retry with a high probability. Moreover, if the variance of service time is large, the negative impact of variance on the delay increases heavily with β because of the frequent energy harvesting. Thus, the blocked users can experience a higher expected delay. In particular, if the service time S is exponentially distributed, we have $Var[S] = 1/\mu_2 < \overline{V}$ because $(R-P)/C > 1/\mu + 1/\theta$. That is, q_e is increasing in β under the exponential distribution.

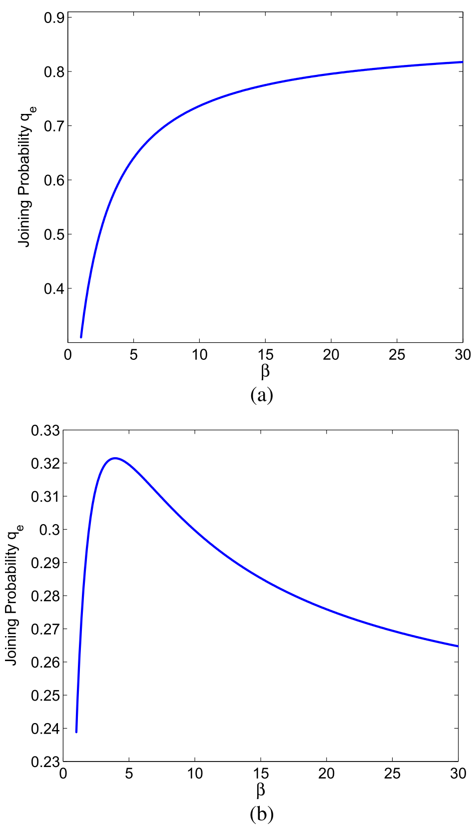

FIGURE 4. **The equilibrium joining probability strategy q_e versus β for $R = 100$, $P = 20$, $\theta = \mu = \lambda = 2$. (a) Var[S] = 10. (b) Var[S] = 60.**

Fig. 4 shows the equilibrium service joining strategy q_e with β under different $Var[S]$. When $Var[S]$ is relatively small, i.e., $Var[S] = 10$, q_e is increasing in β (see Fig. 4(a)). When $Var[S]$ is relatively large, i.e., $Var[S] = 60$, q_e is increasing in $\beta \in (1, 4)$ and then decreasing in $\beta > 4$ (see Fig. 4(b)). In other words, in the IoT system, the energy harvesting rate as well as the service variance have a great impact on the equilibrium service joining strategy of the users. Comparatively, when $Var[S] = E^2[S]$, i.e., S is exponentially distributed, and $\beta \to \infty$, q_e degenerates to the result in [30], then we can summarize the results in Table 1. And we can observe that when the general service time is adopted, q_e can be either larger or smaller than the exponential one, which has been derived in [30]. That is, when the distribution is mistakenly evaluated, the strategy of users will be greatly changed. Also, when the service time is exponential and $\beta < \infty$, we can verify that q_e is increasing in β, then the non-monotone case diminishes.

TABLE 1. **Comparisons with [30] when $R = 30$, $P = 20$, $\beta \to \infty$ and $\theta = \mu = \lambda = 2$.**

$Var[S]$	0	1/4 (i.e., [30])	1
q_e	0.895	0.868	0.789

V. IOT DEVICE's (LEADER's) STRATEGY

In this section, we examine the IoT device's revenue according to the equilibrium service joining strategy of the users that we obtain in Section IV. With the full awareness of the service joining strategy of users, the IoT device can adjust the service price P to achieve its goal. In this regard, when the IoT device charges a high price, few users want to join the waiting orbit, which results in a low revenue. Conversely, when the IoT device charges a low price, many users will wait for the service. However, it can also lead to a low revenue due to the low price. Therefore, it is important for the IoT device to determine an optimal price to maximize its revenue. As we obtain the effective arrival rate, i.e., in (65), we can then derive the IoT device's revenue as follows:

$$f(P) = \lambda_e(P)P, \tag{25}$$

where $\lambda_e(P) = \lambda \cdot (\Pi_0(1) + q_e[\Pi_1(1) + \Pi_2(1)]) = \frac{\beta}{[1-q_e(P)](\lambda+\rho\beta)+\beta}$ is the overall effective arrival rate to system given the equilibrium service joining strategy q_e of the users and service price P (different from the effective arrival rate to λ_{eff} in (65)). It is given as follows:

$$\lambda_e(P) = \frac{\lambda\beta}{[1 - q_e(P)](\lambda + \rho\beta) + \beta}. \tag{26}$$

Therefore, the revenue function of the IoT device can be written as follows:

$$f(P) = \frac{\lambda\mu\beta P}{\lambda[1 - q_e(P)](\mu + \beta) + \mu\beta}. \tag{27}$$

Before determining the optimal price for the IoT device, we give the following lemmas.

Lemma 1: In the IoT system under consideration with $\lambda < \frac{\mu\beta}{\mu+\beta}$, the objective (revenue) function of the IoT device $f(P)$ is concave for $\max\{0, R - CT(1)\} < P \le R - CT(0)$.

Similarly, we can have this property when $\lambda \ge \frac{\mu\beta}{\mu+\beta}$ in the following lemma. Nonetheless, the proof is similar to that of Lemma 1 and hence omitted for brevity.

Lemma 2: In the IoT system with $\lambda \ge \frac{\mu\beta}{\mu+\beta}$, the revenue function of the IoT device $f(P)$ is concave for $0 < P \le R - CT(0)$.

Based on the equilibrium strategy of the users, the concavity of $f(P)$ is established through Lemmas 1-2, which implies that unique price can be found to maximize the payoff of IoT device. To have a better presentation for the optimal prices, we consider two cases according to arrival rate λ in the following subsections: (1) $\lambda < \frac{\mu\beta}{\mu+\beta}$ and (2) $\lambda \geq \frac{\mu\beta}{\mu+\beta}$.

A. OPTIMAL PRICE FOR $\lambda < \frac{\mu\beta}{\mu+\beta}$

We first consider the case with the condition of $\lambda < \frac{\mu\beta}{\mu+\beta}$. We give the optimal price for the IoT device first and then provide its proof.

Theorem 4: In the considered IoT system with energy harvesting and $\lambda < \frac{\mu\beta}{\mu+\beta}$, the revenue of the IoT device and its corresponding optimal price P^*_{ser} that maximizes its revenue can be obtained as follows.

1) For $R < CT(0)$, we have

$$P^*_{\text{ser}} = R. \tag{28}$$

2) For $CT(0) \leq R < CT(1)$, we have

$$P^*_{\text{ser}} = \begin{cases} R, & \text{if } R - CT(0) < P \leq R, \\ P', & \text{if } 0 < P \leq R - CT(0), \end{cases} \tag{29}$$

with $f^*(P) = \max\{f(R), f(P')\}$ where P' satisfies the first-order condition for optimality, i.e.,

$$\lambda_e(P) + P\frac{d\lambda_e(P)}{dP} = 0, \tag{30}$$

for $P \in (0, R - CT(0)]$. Otherwise, $P' = R - CT(0)$.

3) For $CT(1) \leq R < \infty$, we have

$$P^*_{\text{ser}} = \begin{cases} R, & \text{if } R - CT(0) < P \leq R, \\ P^\dagger, & \text{if } R - CT(1) < P \leq R - CT(0), \\ R - CT(1), & \text{if } 0 < P \leq R - CT(0), \end{cases} \tag{31}$$

with $f^*(P) = \max\{f(R), f(P^\dagger), f(R - CT(1))\}$, where $P^\dagger$ satisfies the first-order condition for optimality, i.e.,

$$\lambda_e(P) + P\frac{d\lambda_e(P)}{dP} = 0, \tag{32}$$

for $P \in (R - CT(1), R - CT(0)]$. Otherwise, $P^\dagger = R - CT(0)$.

Next, we consider the counterpart, i.e., when λ is large.

B. OPTIMAL PRICE FOR $\lambda \geq \frac{\mu\beta}{\mu+\beta}$

When $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, the major steps are similar to the analysis of $\lambda \geq \frac{\mu\beta}{\mu+\beta}$. The only difference is that there exists $q(P_0) \in (0, 1]$ such that $T(q(P_0^-)) = \infty$ for $\lambda \geq \frac{\mu\beta}{\mu+\beta}$. Thus, the condition $R \geq CT(1)$ is never active. The following theorem gives the optimal price for the IoT device in this case.

Theorem 5: In the considered IoT system with energy harvesting and $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, the revenue of IoT device and its corresponding optimal price P^*_{ser} that maximizes the revenue of the IoT device can be determined as follows.

1) For $R < CT(0)$, we have

$$P^*_{\text{ser}} = R. \tag{33}$$

2) For $R \geq CT(0)$, we have

$$P^*_{\text{ser}} = \begin{cases} R, & \text{if } R - CT(0) < P \leq R, \\ P', & \text{if } 0 < P \leq R - CT(0), \end{cases} \tag{34}$$

where P' is defined in Theorem 4.

Again, the proof is similar to that of Theorem 4, so it is omitted.

Remark: Theorems 4-5 give the optimal price for IoT device. When R is too small, i.e., $R < CT(0)$, in which all blocked users are not cost-effective to join. Thus the optimal price can be attained at as large as possible: $P^*_{ser} = R$, which is only paid by the users who find an available server. It shows that IoT device will strategically omit blocked users when R is small. On the other hand, when R is large, the optimal price should be carefully selected because multiple pricing strategies are available to Iot device. As the service provider, he can charge a low service fee to serve more users or post a high service fee to serve the unblocked users only (i.e., $P^*_{ser} = R$).

VI. SOCIAL PLANNER's PROBLEM

In Sections IV and V, the IoT device makes the decision as the leader in the Stackelberg game setting to maximize its own revenue. Alternatively, we can consider the IoT device to be a social planner that optimizes the service price so that the social welfare defined in terms of the utility of the users and revenue of the IoT device is maximized. Again, let q denote the service joining probability of the users, $c(q)$ denote the surplus of the users, and $f(q)$ denote the corresponding revenue of the IoT device. They are defined as follows:

$$\begin{aligned} c(q) &= \lambda\Pi_0(1)(R - P) + \lambda q(\Pi_1(1) + \Pi_2(1)) \\ &\quad \times (R - P - CT(q)), \\ f(q) &= (\lambda\Pi_0(1) + \lambda q(\Pi_1(1) + \Pi_2(1)))P, \end{aligned}$$

where $\Pi_1(1)$ and $\Pi_2(1)$ are defined in (12) and (13), respectively. The social welfare is thus defined as follows:

$$\begin{aligned} SW(q) &= c(q) + f(q), \\ &= \frac{\lambda R\mu\beta}{\lambda(1-q)(\mu+\beta) + \mu\beta} \\ &\quad - \frac{\lambda^2 q(\mu+\beta)C}{\theta(\lambda(1-q)(\mu+\beta) + \mu\beta)} \\ &\quad \times \left(1 + \frac{2\mu(\lambda+\rho\beta+\theta)(\mu+\beta) + \mu^2\theta E[S^2]\beta^2}{2(\mu+\beta)(\mu\beta - (\mu+\beta)\lambda q)}\right), \end{aligned}$$

which is a function of q. The social planner wants to motivate the users to adopt the socially-optimal strategy, i.e., the service joining probability q^{soc}, to maximize the social welfare. The social planner can thus set the price to achieve q^{soc} which is also the equilibrium strategy of the users. The next theorem gives the optimal service joining strategy q^{soc}.

$$F(0)=\frac{(\beta\mu+\lambda(\beta+\mu))\left(\beta(\beta+\mu)+\left(\frac{\beta^2\theta E[S^2]\mu}{2}+(\beta+\mu)(\theta+\lambda+\beta\rho)\right)\right)}{\beta^2\theta\mu(\beta+\mu)}, \tag{37}$$

$$F(1)=\frac{\lambda\mu\left(\frac{\beta^2\theta E[S^2]\mu}{2}+(\beta+\mu)(\theta+\lambda+\beta\rho)\right)}{\theta(\beta\mu-\lambda(\beta+\mu))^2}+\frac{(\beta\mu+\lambda(\beta+\mu))\left((\beta+\mu)(\beta\mu-\lambda(\beta+\mu))+\mu\left(\frac{\beta^2\theta E[S^2]\mu}{2}+(\beta+\mu)(\theta+\lambda+\beta\rho)\right)\right)}{\theta\beta\mu(\beta+\mu)(\beta\mu-\lambda(\beta+\mu))}. \tag{38}$$

$$D=\beta\lambda(\beta+\mu)^2(\lambda\mu+\beta(\lambda+\mu-\theta\mu\nu)), \tag{39}$$

$$E=\beta\lambda^2(\beta+\mu)^2\left(\beta^2\lambda+\beta(\theta+2\lambda)\mu+\mu(\frac{\beta^2\theta E[S^2]\mu}{2}+(\theta+\lambda)\mu)\right)\times\left(\frac{\beta^2\theta E[S^2]\mu}{2}(\lambda\mu+\beta(\lambda+\mu))+\theta(\beta+\mu)\left(\lambda\mu+\beta^2\lambda\nu+\beta(\lambda+\mu+\lambda\mu\nu)\right)\right), \tag{40}$$

$$F=\lambda^2(\beta+\mu)^2(A+(\beta+\mu)(\theta+\beta(-1+\theta\nu))). \tag{41}$$

To simplify the notations, we denote $\nu = R/C$ which is the ratio of reward to cost of the user.

Theorem 6: In the considered IoT system with energy harvesting and $\lambda < \frac{\mu\beta}{\mu+\beta}$, the unique optimal strategy q^{soc} of the users that maximizes the social welfare is given by

$$q^{soc}=\begin{cases}0, & \text{if } 0<\nu<F(0),\\ q', & \text{if } F(0)\le\nu\le F(1),\\ 1, & \text{if } F(1)<\nu,\end{cases} \tag{35}$$

where $F(0)$ and $F(1)$ are defined in (37) and (38), as shown at the top of this page, respectively, and

$$q'=\frac{-D-\sqrt{E}}{F}, \tag{36}$$

where D, E and F are given in (39)-(41), as shown at the top of this page.

In Theorem 6, the socially optimal joining probability is uniquely determined, which is dependent on the value of $\nu = R/c$, i.e., the reward-cost ratio. When ν is small, from the perspective of social planner, it is never wise to allow the joining of blocked users because the additional reward brought by them cannot compensate for the increased system congestion that is resulted by them. Therefore, we have $q^{soc} = 0$. On the other hand, when ν is too large, the increased delay cost could be secondary comparing to the improved reward. Thus a high joining probability $q^{soc} = 1$ should be adopted.

Remark: For the case of $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, similar to Theorem 6, the unique socially-optimal service joining strategy q^{soc} is given by

$$q^{soc}=\begin{cases}0, & \text{if } 0<\nu<F(0),\\ q', & \text{if } F(0)\le\nu,\end{cases} \tag{42}$$

where q' and $F(0)$ are given in (36) and (37), respectively.

The social planner needs to find the optimal price for the optimal strategy q^{soc}. The corresponding optimal price P^* for the case of $\lambda < \frac{\mu\beta}{\mu+\beta}$ is given in the following theorem.

Theorem 7: In the considered IoT system with energy harvesting and $\lambda < \frac{\mu\beta}{\mu+\beta}$, the socially-optimal price that maximizes the social welfare is given by

$$P^*_{\text{soc}}=\begin{cases}C(F(0)-T(0)), & \text{if } 0<\nu<F(0),\\ R-C\left(\frac{\beta+(1-q')(\lambda+\rho\beta)}{\theta(\beta-\lambda q'-\rho q'\beta)}+\frac{\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)(\beta-\lambda q'-\rho q'\beta)}\right), & \text{if } F(0)\le\nu\le F(1),\\ C(F(1)-T(1)), & \text{if } F(1)<\nu,\end{cases} \tag{43}$$

where $F(0)$, $F(1)$ and q' are, respectively, given by (37), (38) and (36), and $T(q)$ is the expected waiting time for the users.

Remark: For the case of $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, the socially-optimal price is given by

$$P^*_{\text{soc}}=\begin{cases}C(F(0)-T(0)), & \text{if } 0<\nu<F(0),\\ \text{R-C}\left(\frac{1}{\theta}+\frac{\lambda+\rho\beta}{\theta(\beta-\lambda q'-\rho q'\beta)}+\frac{\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)(\beta-\lambda q'-\rho q'\beta)}\right), & \text{if } F(0)\le\nu\le F(1).\end{cases} \tag{44}$$

The proof is again similar to that of Theorem 7, and it is omitted.

In Sections V and VI, we show that in the IoT system with energy harvesting, a unique price can be set to maximize the revenue of the IoT device and the social welfare, respectively. However, there exists a difference between the two prices P^*_{ser} and P^*_{soc}. In Section VII, we examine the difference in terms of the Price of Anarchy (PoA).

VII. THE PRICE OF ANARCHY

The Price of Anarchy (PoA) is a measure for the loss of optimality due to self-interest behavior. As we obtain the optimal social welfare under a certain price P^*_{soc} (Section VI) proposed by the IoT device, we can also obtain the social welfare with the 'worst equilibrium' which can be derived through a corresponding price P. Here, the PoA is defined as the ratio of the expected optimal welfare SW^* to the expected social welfare SW^{w} under the 'worst equilibrium'. Define q_0 as the unique solution of $R - CT(q_0) = 0$. Notice that $q_0 \leq 1 \Leftrightarrow \nu \leq \frac{\beta+\theta+\frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)}}{(\beta(1-\rho)-\lambda)\theta} = \overline{\nu}$, then we have the following lemma.

Lemma 3: In the considered IoT system with energy harvesting and $\lambda < \frac{\mu\beta}{\mu+\beta}$, a unique service joining strategy q^{w} that makes the social welfare the worst, given that the users adopt an equilibrium strategy, is given as follows.

- For $\nu \leq \overline{\nu}$, we have

$$q^{\text{w}} = \begin{cases} q_0 & \text{if } 0 < \nu < F(0), \\ \arg\min_q\{SW(q=0), SW(q=q_0)\}, \\ \quad \text{if } F(0) \leq \nu \leq F(1), \\ 0, & \text{if } F(1) < \nu. \end{cases} \tag{45}$$

- For $\nu > \overline{\nu}$, we have

$$q^{\text{w}} = \begin{cases} 1, & \text{if } 0 < \nu < F(0), \\ \arg\min_q\{SW(q=0), SW(q=1)\}, \\ \quad \text{if } F(0) \leq \nu \leq F(1), \\ 0, & \text{if } F(1) < \nu, \end{cases} \tag{46}$$

where

$$SW(0) = \frac{\lambda R\mu\beta}{\lambda(\mu+\beta)+\mu\beta},$$

$$SW(1) = \lambda R - \frac{\lambda^2 C}{\theta\mu\beta}\left(\frac{(\theta+\beta)(\mu+\beta)\mu + \frac{\beta^2\mu^2\theta E[S^2]}{2}}{\mu\beta-(\mu+\beta)\lambda}\right),$$

$$SW(q_0) = \frac{\lambda R(\lambda+\rho\beta+\theta+\frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})}{\left(\lambda+\rho\beta+\theta+\frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)}\right)+(\lambda+\rho\beta)(R\theta-1)}.$$

Based on the definition of PoA, we have

$$PoA(\lambda,\mu,\nu,\theta,\beta) = \frac{SW(q^{soc})}{SW(q^{\text{w}})}. \tag{47}$$

Theorem 8: In the considered IoT system with energy harvesting and $\lambda < \frac{\mu\beta}{\mu+\beta}$, the PoA is obtained as follows.

1) For $\overline{\nu} < F(0)$, we have

$$PoA(\lambda,\mu,\nu,\theta,\beta) = \begin{cases} \frac{SW(0)}{SW(q_0)}, & \text{if } \nu < \overline{\nu}, \\ \frac{SW(0)}{SW(1)}, & \text{if } \overline{\nu} \leq \nu < F(0), \\ \frac{SW(q')}{\min\{SW(0), SW(1)\}}, & \text{if } F(0) \leq \nu < F(1), \\ \frac{SW(q')}{SW(0)}, & \text{if } F(1) \leq \nu. \end{cases} \tag{48}$$

2) For $\overline{\nu} \geq F(0)$, we have

$$PoA(\lambda,\mu,\nu,\theta,\beta) = \begin{cases} \frac{SW(0)}{SW(q_0)}, & \text{if } \nu < F(0), \\ \frac{SW(q')}{\min\{SW(0), SW(q_0)\}}, & \text{if } F(0) \leq \nu < \overline{\nu}, \\ \frac{SW(q')}{\min\{SW(0), SW(1)\}}, & \text{if } \overline{\nu} \leq \nu < F(1), \\ \frac{SW(q')}{SW(0)}, & \text{if } F(1) \leq \nu. \end{cases} \tag{49}$$

Based on the results in Theorem 6 and Lemma 3, we have the corresponding q^{soc} and q^{w} in each subcase, respectively. And the PoA can be derived by substituting them into $SW(q^{soc})/SW(q^{\text{w}})$.

In particular, it is not difficult to verify that for $\nu \to \infty$, we have $\lim_{\nu\to\infty} PoA(\lambda,\mu,\nu,\theta,\beta) = SW(1)/SW(0) = 1+\frac{(\mu+\beta)\lambda}{\mu\beta}$. It is interesting to find that the PoA is independent of θ when ν is great enough. Specifically, for $\beta \to \infty$, we can obtain the same result as [32, Lemma 3.1], which is $\lim_{\nu\to\infty} PoA = 1+\rho$. The limit results provide an intuition that the PoA could be quite large when ν increases. Thus it is imperative to regulate the joining strategy of users for social planner so as to maximize the social welfare.

Analogically, note that for $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, we must have $q_0 < 1$. Then, it is not necessary to consider $\overline{\nu}$, which is defined before Lemma 3.

Remark: For $\lambda \geq \frac{\mu\beta}{\mu+\beta}$, a unique mixed service joining strategy q^{w} that makes the social welfare the worst is given by

$$q^{\text{w}} = \begin{cases} q_0, & \text{if } 0 < \nu < F(0), \\ \arg\min_q\{SW(q=0), SW(q=q_0)\}, \\ \quad \text{if } F(0) \leq \nu. \end{cases} \tag{50}$$

The corresponding PoA is

$$PoA(\lambda,\mu,\nu,\theta,\beta) = \begin{cases} \frac{SW(0)}{SW(q_0)}, & \text{if } 0 < \nu < F(0), \\ \frac{SW(q')}{\min\{SW(0), SW(q_0)\}}, & \text{if } \nu \geq F(0). \end{cases} \tag{51}$$

VIII. PERFORMANCE EVALUATION

In this section, we perform some numerical experiments to illustrate the effects of the parameters on the pricing of the IoT device. Specifically, we explore the sensitivity of the revenue-maximizing as well as the socially-optimal prices with respect to the given parameters, μ, λ, θ, and β (Section VIII.A). Furthermore, the sensitivity of equilibrium joining probability and the results for PoA are illustrated in Section VIII.B and Section VIII.C, respectively, to verify our theoretical analysis presented in Section VII.

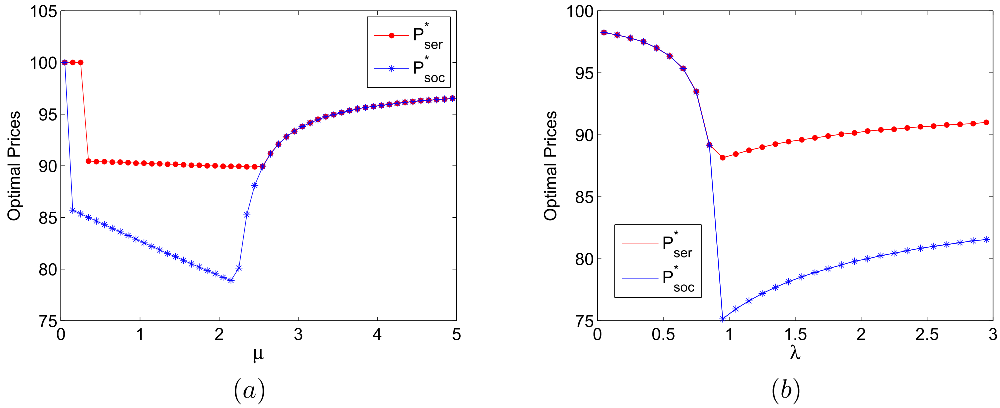

FIGURE 5. (a) Revenue-maximizing and socially-optimal prices versus service rate μ for $R = 100$, $\theta = \beta = 2$ and $\lambda = 1$ and (b) the prices versus arrival rate λ for $R = 100$, $\theta = \beta = \mu = 2$.

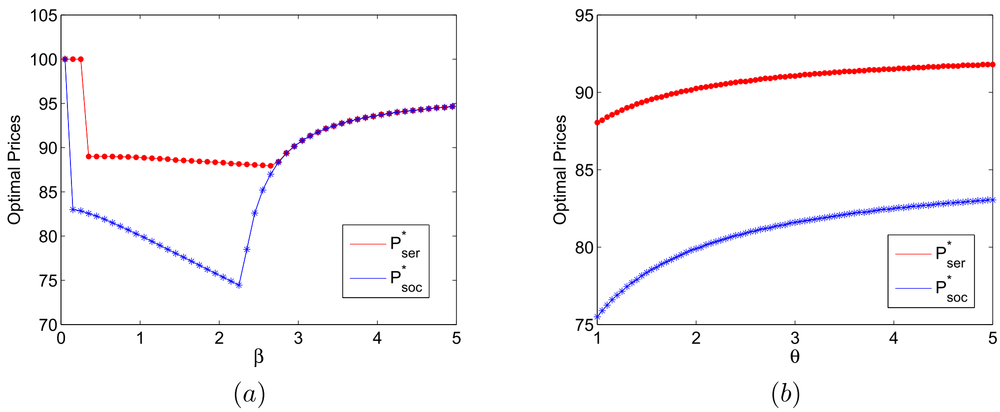

FIGURE 6. (a) Revenue-maximizing and socially-optimal prices versus energy harvesting rate β for $R = 100$, $\lambda = 1$, and $\mu = \theta = 2$ and (b) the prices versus retrial rate θ for $R = 100$, $\lambda = \mu = \beta = 2$.

A. THE COMPARISON BETWEEN THE REVENUE-MAXIMIZING AND THE SOCIALLY-OPTIMAL PRICES OF THE IoT DEVICE

In Fig. 5(a), we observe that P^*_{ser} and P^*_{soc} are not monotone in μ. In particular, for $\mu \in [0.5, 2]$, both P^*_{ser} and P^*_{soc} are non-increasing in μ. The reason is that when μ increases, the IoT device can serve more users. By setting a lower price, more users are attracted to the service for both revenue-maximizing and the socially-optimal pricing. For $\mu > 2$, the users are more inclined to join the waiting orbit, and thus the IoT device applying the socially-optimal pricing will charge a higher price to decrease the service joining probability of the users. This is to avoid performance degradation which leads to a smaller social welfare. Meanwhile, when μ is large enough, more users are willing to join the waiting orbit and retry to access the IoT device. Therefore, the IoT device applying revenue-maximizing pricing can also charge the users a higher price to maximize its revenue. As such, both P^*_{ser} and P^*_{soc} are increasing in μ.

Similarly, in Fig. 5(b), P^*_{ser} and P^*_{soc} are not monotone in λ. For $\lambda > \frac{\mu\beta}{\mu+\beta}$, i.e., λ is larger than one, both P^*_{ser} and P^*_{soc} are increasing in λ. This is consistent with the observation

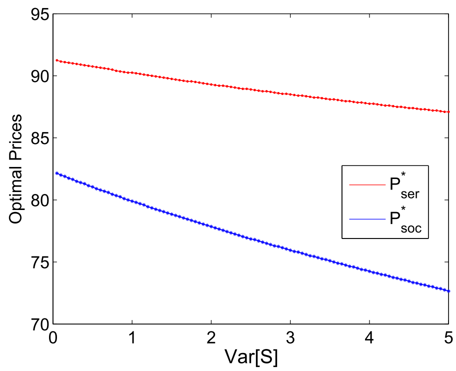

FIGURE 7. Revenue-maximizing and socially-optimal prices versus $Var[S]$ for $R = 100$, $\lambda = \mu = \theta = \beta = 2$.

in Fig. 5(a), where P^*_{ser} and P^*_{soc} are non-increasing in μ for $\lambda > \frac{\mu\beta}{\mu+\beta}$. In this case, the IoT device applying revenue-maximizing and socially-optimal pricing has an incentive to set a higher price. On the contrary, for $\lambda \leq \frac{\mu\beta}{\mu+\beta}$, both P^*_{ser} and P^*_{soc} are non-increasing in λ, and the opposite result can be found in Fig. 5(a). The IoT device uses a low

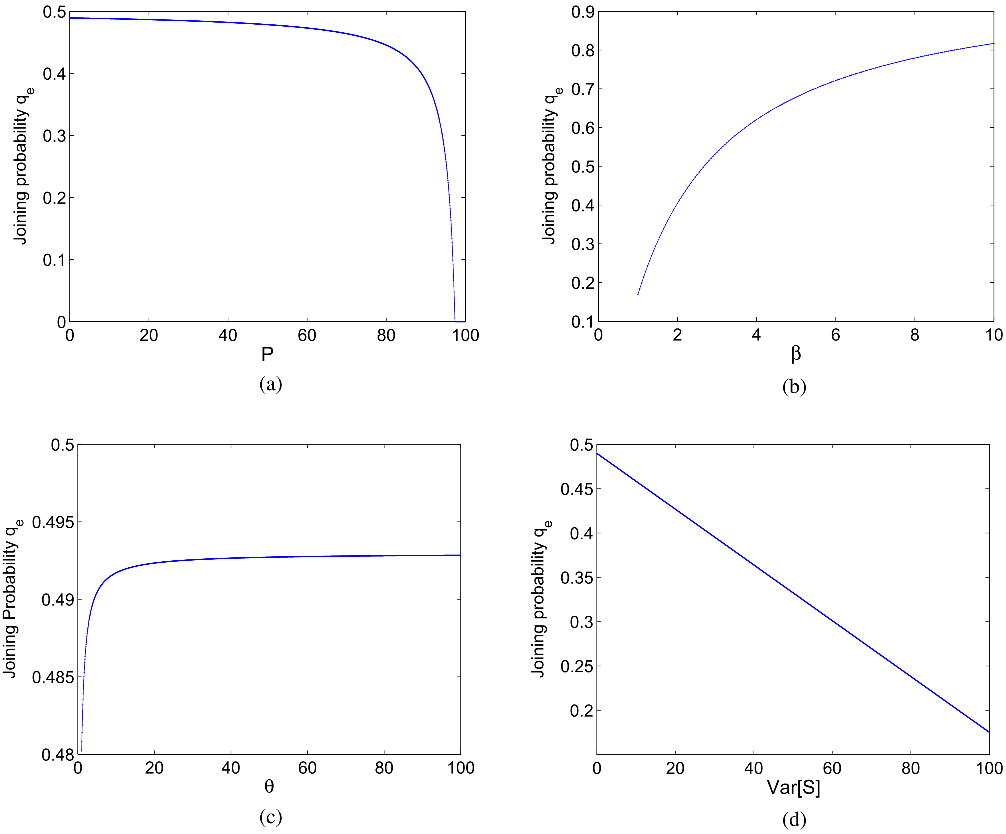

FIGURE 8. The effective joining probability versus P, β, θ and $Var[S]$ for $R = 100$, and $\lambda = \mu = 2$. (a) $\beta = \theta = Var[S] = 2$. (b) $\theta = Var[S] = 2$, $P = 20$. (c) $\beta = Var[S] = 2$, $P = 20$. (d) $\beta = \theta = 2$, $P = 20$.

price to encourage a higher service joining probability of the users.

Interestingly, the effect of β on the prices is almost the same as the effect of μ, as shown in Fig. 6(a). For $\lambda > \frac{\mu\beta}{\mu+\beta}$, both P^*_{ser} and P^*_{soc} are non-increasing in β. The reason is that when β is too low, the energy harvesting time is long, and then the users are reluctant to join the waiting orbit. Consequently, the IoT device applying revenue-maximizing and socially-optimal pricing wants to set a lower price to attract more users. On the contrary, the IoT device will charge a higher price to maximize its revenue because the users are more likely to join the waiting orbit. The similar effect of β and μ is from the fact that the energy harvesting delay and the service time can be regarded as a service delay in general. Therefore, when the delay is shorter, the users are likely to join the orbit and wait for the service from the IoT device.

When the retrial rate θ increases, the waiting time of the users in the orbit decreases, and it results in a less waiting cost to the users. The IoT device applying revenue-maximizing and socially-optimal pricing will benefit from setting a higher price. As shown in Fig. 6(b), P_{ser} and P_{soc} are increasing in θ. The retrial rate θ can be interpreted as the repeating frequency of the users. Thus, when θ is large, the users retry to access the IoT device more frequently which results in higher prices to maximize social welfare as well as the revenue.

Fig. 7 shows that both P^*_{ser} and P^*_{soc} are decreasing with $Var[S]$. The reason is that when $Var[S]$ increases, the mean waiting time of the blocked users increases. Therefore, fewer users are willing to join the waiting orbit. The IoT device needs to charge a lower price to attract more users.

In summary, through Figs. 5-7, we can always have $P^*_{\text{ser}} \geq P^*_{\text{soc}}$. That is, to maximize the IoT device's revenue, the IoT device with revenue-maximizing pricing will set a higher price than that of the socially-optimal pricing. This results in a lower service joining probability, i.e., $q_{\text{ser}} \leq q_{\text{soc}}$ because q_{e} is decreasing in P. In other words, the socially-optimal pricing allows more users to join the waiting orbit to maximize the social welfare. However, to meet the revenue-maximizing pricing, the higher price diminishes the users' surplus, which results in a lower service joining probability. Such results agree with similar results concerning the economic analysis of other queuing models, e.g., [33].

B. EVALUATION ON EFFECTIVE SERVICE JOINING PROBABILITY

We next examine the effective service joining probability of the users. Fig. 8 shows the effects of parameters P, β, θ and $Var[S]$ on effective service joining probability q_{e}.

Consistent with our intuition, q_e is decreasing with price P and $Var[S]$. When P approaches 100, q_e drops to 0 sharply. Meanwhile, we find that q_e is linear to $Var[S]$. The reason is that the waiting time $T(q)$ is linear to $Var[S]$. On the other hand, we also observe that q_e is increasing in β and θ. The reason is that the increase of q_e leads to the decrease of the waiting time of the users when $Var[S]$ is small.

C. EVALUATION ON PRICE OF ANARCHY (PoA)

We investigate the PoA to verify the theoretical findings presented in Section VII. From Fig. 9, the PoA increases with the increase of ν, where $\nu = R/C$ is the ratio between the reward and cost of the user. Recall our analytical finding that when ν is high enough, the PoA approaches $1 + \frac{\lambda(\beta+\mu)}{\beta\mu}$. In this case, we also find that the PoA approaches 2 when ν increases, which is consistent with the finding.

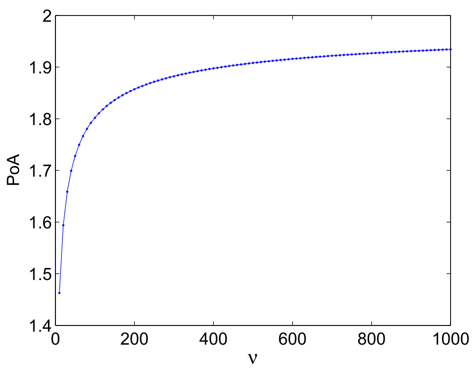

FIGURE 9. PoA versus ν for $\lambda = 1$ and $\mu = \theta = \beta = 2$.

IX. CONCLUSION

We have considered an IoT system in which the IoT device is equipped with energy harvesting capability. The IoT device charges a service price to the IoT users and the users which find that the IoT device is unavailable, i.e., when it is serving the other user or harvesting energy, can probabilistically join the waiting orbit and retry to access the IoT device later. We have proposed a joint queuing and game theoretic model to analyze the service pricing and user service joining strategy. We have considered the scenario that the IoT device is the leader of the Stakelberg game adjusting the service price to maximize its revenue being aware that the users will choose their strategy such that their utility is maximized. We have also extended the analysis considering the scenario that the IoT device acts as a social planner adjusting the service price to maximize a social welfare that is the sum of its revenue and users' utility. The extensive analyses have been presented which reveal many important findings regarding the effects of system parameters to the strategies of the IoT device and the users. For the future work, it is meaningful to study the strategic behavior of users in the IoT device which can serve multiple users, and the heterogeneous users who have different preference on the IoT device can be considered.

APPENDIX

A. PROOFS

Proof of Theorem 1: Multiplying equations (7)-(10) by z^i and summing up over all i, we derive the following basic equations after some manipulations, i.e.,

$$\lambda\Pi_0(z) + \theta z\frac{d\Pi_0(z)}{dz} = \beta\Pi_2(z), \tag{52}$$

$$\frac{\partial\Pi_1(z,x)}{\partial x} = -(\lambda q - \lambda qz + b(x))\Pi_1(z,x), \tag{53}$$

$$\Pi_1(z,0) = \lambda\Pi_0(z) + \theta\frac{d\Pi_0(z)}{dz}, \tag{54}$$

$$(\lambda q - \lambda qz + \beta)\Pi_2(z) = \int_0^\infty p_1(z,x)b(x)dx. \tag{55}$$

Solving the differential equation in (53), we have

$$\Pi_1(z,x) = \Pi_1(z,0)(1-B(x))e^{-(\lambda q-\lambda qz)x}. \tag{56}$$

Substituting (56) into (55), we obtain

$$(\lambda q - \lambda qz + \beta)\Pi_2(z) = \Pi_1(z,0)k(z), \tag{57}$$

where $k(z) = \int_0^\infty(1-B(x))b(x)e^{-(\lambda q-\lambda qz)x}dx$. Substituting $\Pi_2(z)$ into (52), we get

$$\frac{\beta k(z)}{\lambda q - \lambda qz + \beta}\Pi_1(z,0) = \lambda\Pi_0(z) + \theta z\frac{d\Pi_0(z)}{dz}. \tag{58}$$

Eliminating $\frac{d\Pi_0(z)}{dz}$ in (58) by combining (54), we have

$$\left(\frac{\beta k(z)}{\lambda q - \lambda qz + \beta} - z\right)\Pi_1(z,0) = \lambda\Pi_0(z)(1-z). \tag{59}$$

The expressions in (56) and (59) allow us to derive $\Pi_1(z,x)$ as follows:

$$\Pi_1(z,x) = \frac{\lambda\Pi_0(z)(1-z)}{\frac{\beta k(z)}{\lambda q-\lambda qz+\beta} - z}(1-B(x))e^{-(\lambda q-\lambda qz)x}. \tag{60}$$

Denote $\alpha(s) = \int_0^\infty e^{-sx}dB(x)$ as the Laplace-Stieltjes transformation of $B(x)$ and $\alpha_k = (-1)^k\alpha^{(k)}(0)$, we integrate (60) with respect to x. Using the well known formula (see p.10 of [7]), it gives

$$\int_0^\infty e^{-sx}(1-B(x))dx = \frac{1-\alpha(s)}{s}, \tag{61}$$

we obtain

$$\Pi_1(z) = \frac{1-\alpha(\lambda q(1-z))}{(\frac{\beta k(z)}{\lambda q-\lambda qz+\beta} - z)q}\Pi_0(z). \tag{62}$$

Eliminating $\Pi_1(z,0)$ through (54) and (58), we have

$$\Pi_0'(z) = \frac{\lambda\left(1 - \frac{\beta k(z)}{\lambda q-\lambda qz+\beta}\right)}{\left(\frac{\beta k(z)}{\lambda q-\lambda qz+\beta} - z\right)\theta}\Pi_0(z). \tag{63}$$

By solving the above differential equation, we have

$$\Pi_0(z) = \Pi_0(1)\exp\left(\frac{\lambda}{\theta}\int_1^z \frac{1-\frac{\beta k(u)}{\lambda q-\lambda qu+\beta}}{\frac{\beta k(u)}{\lambda q-\lambda qu+\beta} - u}du\right). \tag{64}$$

It is noted that $\frac{\mathrm{d}k(z)}{\mathrm{d}z}|_{z=1} = \lambda q \int_0^\infty x dB(x) = \rho q$. Then, by letting $z \to 1$, combining (64), (62), and (52) and using the normalization condition $\Pi_0(1) + \Pi_1(1) + \Pi_2(1) = 1$, we obtain (11)-(13) immediately.

Next, to obtain the number of users in the waiting orbit, we take the derivative of the expression in (64) with respect to z at the point $z = 1$. Then, we obtain the value of $N_0 = \Pi_0'(1)$ which yields (14). In a similar way, we can obtain N_2 and N_1 through (52) and (62), respectively. We also have $N = \sum_{i=0}^{2} N_i$ which is the total average number of users in the system. Therefore, the average waiting time can be computed with the use of the Little's formula. Notice that the effective arrival rate of users to the waiting orbit is

$$\lambda_{\text{eff}} = \lambda q(1 - \Pi_0(1)). \tag{65}$$

By using Little's law, we obtain the average waiting time $T(q) = \frac{N}{\lambda_{\text{eff}}}$ as in (17). Since $T(q) = \frac{1}{\theta} + \frac{\lambda+\rho\beta}{\theta(\beta-\lambda q-\rho q\beta)} + \frac{\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}$, which is a function of q, the numerators of the second term and the third term are constant with respect to q. When the system is stable, we have $(\beta - \lambda q - \rho q\beta) > 0$. By taking the derivative of $T(q)$ with respect to q, we have

$$\frac{\mathrm{d}T(q)}{\mathrm{d}q} = \frac{(\lambda + \rho\beta)^2}{\theta(\beta - \lambda q - \rho q\beta)^2} + \frac{\lambda + \rho\beta + \frac{\lambda E[S^2]\beta^2}{2}}{(\beta - \lambda q - \rho q\beta)^2} > 0.$$

Thus, $T(q)$ is increasing in q. This completes our proof. ■

Proof of Theorem 2: Since $T(q)$ is strictly increasing for $q \in [0, 1]$ from Theorem 1, the expected utility $U(q) = R - P - CT(q)$ is strictly decreasing for q. As we have mentioned before, q_e can characterize an equilibrium if and only if $\arg\min_{\hat{q}\in[0,1]} U(\hat{q}; q_e) = q_e$. Notice that when the user who finds a unavailable server chooses to balk, her utility is 0. We can derive the equilibrium q_e by considering the following cases.

1) For the case of $\lambda < \frac{\mu\beta}{\mu+\beta}$, we have the following subcases.
   - When $(R - P)/C \in (0, T(0))$, the expected utility for users $U(q)$ is negative for every q, i.e., $U(q) < 0$ for $q \in [0, 1]$. Consequently, the best response is not to wait in the orbit, i.e., $\hat{q} = 0$, and the unique Nash equilibrium strategy is $q_\mathrm{e} = 0$.
   - When $(R - P)/C \in [T(0), T(1)]$, we have $U(0) > 0$ and $U(1) < 0$, thus there exists a unique solution $q_e \in (0, 1)$ of the equation $U(q_\mathrm{e}) = 0$ because $U(q)$ is decreasing in $q \in [0, 1]$. In this case, when all other users adopt strategy q_e, we have $\hat{q}U(q_e) = 0$ for all $\hat{q} \in [0, 1]$, which gives $\hat{q}U(q_e) \le q_eU(q_e)$. That is, q_e is the unique Nash equilibrium strategy.
   - When $(R - P)/C \in (T(1), \infty)$, the expected utility $U(1)$ is positive. Therefore, we have $\hat{q}U(1) > 0$ for any $\hat{q} \in (0, 1]$, which implies that joining with probability 1 is the best response for each blocked user, i.e., we have $q_\mathrm{e} = 1$.

2) For the case of $\lambda \ge \frac{\mu\beta}{\mu+\beta}$, notice that $\lim_{q\to\beta/(\lambda+\rho\beta)} T(q) = \infty$, which implies that $\lim_{q\to\beta/(\lambda+\rho\beta)} U(q) = -\infty$. Since $\beta/(\lambda + \rho\beta) < 1$, we must have $q_\mathrm{e} < 1$. Recall that $U(q)$ is strictly decreasing in $q \in [0, \beta/(\lambda + \rho\beta))$, we have the following subcases.
   - When $(R - P)/C \in (0, T(0))$, the expected utility for users $U(q)$ is negative for every $q \in (0, \beta/(\lambda + \rho\beta))$, i.e., $U(q) < 0$ for all $q \in [0, \beta/(\lambda + \rho\beta))$. Consequently, the best response is not to join the orbit, and the unique equilibrium is $q_\mathrm{e} = 0$.
   - When $(R - P)/C > (T(0), \infty)$, we have $U(0) < 0$ and $\lim_{q\to\beta/(\lambda+\rho\beta)} U(q) = -\infty$, thus there exists unique Nash equilibrium $q_e \in (0, \beta/(\lambda+\rho\beta))$ such that $U(q_\mathrm{e}) = 0$ by noticing that $U(q)$ is decreasing in $q \in [0, \beta/(\lambda + \rho\beta))$. ■

Proof of Theorem 3: In 1) (above), it is sufficient to show that $T(q)$ is decreasing in θ for every $q \in [0, 1]$. Notice that $\beta > \lambda q + \rho q\beta$, then we have $\frac{\lambda+\rho\beta}{\theta^2(\beta-\lambda q-\rho q\beta)} > 0$, which gives

$$\frac{\partial T(q)}{\partial\theta} = -\frac{1}{\theta^2} - \frac{\lambda + \rho\beta}{\theta^2(\beta - \lambda q - \rho q\beta)} < 0,$$

which implies that $T(q)$ decreases with θ, and $U(q)$ increases with θ. As $U(q)$ is decreasing in $q[0, 1]$, we can conclude that q_e is increasing in θ.

In 2) (above), consider the service joining probability

$$q_\mathrm{e} = \frac{[(R - P)\theta - C]\beta - (\lambda + \rho\beta + \theta + \frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})C}{[(R - P)\theta - C](\lambda + \rho\beta)},$$

by taking the derivative with respect to β, we have

$$\frac{\partial q_\mathrm{e}}{\partial\beta} = \frac{\mu^2((R - P)\theta(\beta+\mu) - C(\beta-\theta + \mu + V\beta\theta\mu))}{((R - P)\theta - C)\lambda(\beta + \mu)^3} > 0,$$
$$\Leftrightarrow ((R-P)\theta-C(1+V\theta\mu))\beta > C(\mu-\theta)-(R-P)\theta\mu.$$

Since $C(\mu - \theta) - (R - P)\theta\mu < 0$, if $(R - P)\theta - C(1 + V\theta\mu) > 0$, i.e., $Var[S] < \overline{V}$, we have $\partial q_\mathrm{e}/\partial\beta > 0$ for $\beta > 0$, and thus q_e is increasing in β. If $(R - P)\theta - C(1 + V\theta\mu) < 0$ (i.e., $Var[S] > \overline{V}$), we have

$$\frac{\partial q_\mathrm{e}}{\partial\beta} > 0 \Leftrightarrow \beta < \frac{C(\mu - \theta) - (R - P)\theta\mu}{(R - P)\theta - C(1 + V\theta\mu)},$$
$$\frac{\partial q_\mathrm{e}}{\partial\beta} < 0 \Leftrightarrow \beta > \frac{C(\mu - \theta) - (R - P)\theta\mu}{(R - P)\theta - C(1 + V\theta\mu)}.$$

That is, q_e is increasing in β first, and then decreasing in β. ■

Proof of Lemma 1: From Theorem 2, when $\max\{0, R - CT(1)\} < P \le R-CT(0)$, the equilibrium joining probability is given as follows:

$$q_\mathrm{e} = \frac{\beta}{\lambda + \rho\beta} - \frac{(\lambda + \rho\beta + \theta + \frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})C}{[(R - P)\theta - C](\lambda + \rho\beta)},$$

which is decreasing and concave in P from

$$\frac{\mathrm{d}q_\mathrm{e}(P)}{\mathrm{d}P} = -\frac{\theta(\lambda + \rho\beta + \theta + \frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})C}{[(R - P)\theta - C]^2(\lambda + \rho\beta)} < 0,$$

$$\frac{\mathrm{d}^2 q_\mathrm{e}(P)}{\mathrm{d}P^2} = -\frac{2\theta^2(\lambda+\rho\beta+\theta+\frac{\lambda E[S^2]\beta^2\theta}{2(\lambda+\rho\beta)})C}{[(R-P)\theta-C]^3(\lambda+\rho\beta)} < 0.$$

Taking the first and the second derivatives of $\lambda_\mathrm{e}(P)$ in a similar way, we can obtain

$$\frac{\mathrm{d}\lambda_\mathrm{e}(P)}{\mathrm{d}P} = \frac{\lambda^2\mu\beta(\mu+\beta)}{(\lambda(1-q)(\mu+\beta)+\mu\beta)^2}\frac{\mathrm{d}q_\mathrm{e}(P)}{\mathrm{d}P} < 0,$$

$$\frac{\mathrm{d}^2\lambda_\mathrm{e}(P)}{\mathrm{d}P^2} = \frac{\lambda^2\mu\beta(\mu+\beta)}{(\lambda(1-q)(\mu+\beta)+\mu\beta)^2}\frac{\mathrm{d}^2 q_\mathrm{e}(P)}{\mathrm{d}P^2} + \frac{2\lambda^3\mu\beta(\mu+\beta)^2}{(\lambda(1-q)(\mu+\beta)+\mu\beta)^3}\frac{\mathrm{d}q_\mathrm{e}(P)}{\mathrm{d}P} < 0.$$

Therefore, the second-order condition of the revenue function for the IoT device satisfies

$$\frac{\mathrm{d}^2 f(P)}{\mathrm{d}P^2} = P\frac{\mathrm{d}^2\lambda_\mathrm{e}(P)}{\mathrm{d}P^2} + 2\frac{\mathrm{d}\lambda_\mathrm{e}(P)}{\mathrm{d}P} < 0.$$

This completes the proof. ■

Proof of Theorem 4: Notice that the revenue of the IoT device can be derived immediately from Theorem 2 and (27). For the optimal price P^*, we have the three corresponding cases.

1) If $R < CT(0)$, i.e., for a blocked user that decides to enter the waiting orbit without other users in the orbit if the expected waiting time is more than the reward that the blocked user gains from the service, then the blocked user never joins the orbit even if there is no price imposed. Thus, the best response is $q_\mathrm{e}(P) = 0$ for any price P. The IoT device's revenue is $f(P) = \frac{\lambda\mu\beta P}{\lambda(\mu+\beta)+\mu\beta}$. Therefore, the price can be set to R.

2) If $R - CT(1) < 0$, the IoT device's revenue is given by

$$f(P) = \begin{cases} \dfrac{\lambda\mu\beta P}{\lambda(\mu+\beta)+\mu\beta}, & \text{if } R-CT(0) < P \le R, \\ \dfrac{\lambda\mu\beta P}{\lambda[1-q_\mathrm{e}(P)](\mu+\beta)+\mu\beta}, & \text{if } 0 < P \le R-CT(0). \end{cases}$$

Since $f(P)$ is concave for $P \in (0, R-CT(0)]$ from Lemma 1. Thus, there exists at most one stationary point that satisfies the first-order condition in (30). However, the extreme point may not be in the interval $(0, R-CT(0)]$. If $P' \in (0, R-CT(0)]$, it is the optimal point. Otherwise, the optimal point is $R-CT(0)$ because the other end point $P = 0$ yields zero revenue to the IoT device. For $P \in (R-CT(0), R]$, we have $U(0) < 0$, and thus $q_\mathrm{e}(P) = 0$. Similar to the case in 1) above, the price can be set to R.

3) If $R - CT(1) \ge 0$, the IoT device's revenue is given by

$$f(P) = \begin{cases} \dfrac{\lambda\mu\beta P}{\lambda(\mu+\beta)+\mu\beta}, & \text{if } R-CT(0) < P \le R, \\ \dfrac{\lambda\mu\beta P}{\lambda[1-q_\mathrm{e}(P)](\mu+\beta)+\mu\beta}, & \text{if } R-CT(1) < P \le R-CT(0), \\ \lambda P, & \text{if } 0 < P \le R-CT(0), \end{cases}$$

for $P \in (0, R-CT(1)]$, we have $q_\mathrm{e}(P) = 1$. Then, the optimal price is $R-CT(1)$. For $P \in (R-CT(1), R-CT(0)]$ and $P \in (R-CT(0), R]$, the optimal price P^*_ser can be derived in a similar way to the case in 2) above, so we omit it here. ■

Proof of Theorem 6: Differentiating $SW(q)$ with respect to q, we have

$$\frac{\mathrm{d}SW(q)}{\mathrm{d}q} = \frac{\lambda^2(\mu+\beta)\beta\mu C}{(\beta\mu+(1-q)\lambda(\mu+\beta))^2}(\nu - F(q)), \quad (66)$$

where $F(q)$ is given in (67), as shown at the top of the next page. To investigate the monotonicity of $SW(q)$, we need to examine the monotonicity of $\nu - F(q)$ by taking the derivative of $F(q)$. Accordingly, we can derive (68), as shown at the top of the next page. It is straightforward to find that $\frac{\mathrm{d}F(q)}{\mathrm{d}q} > 0$, and thus $F(q)$ is monotonically increasing in q. We thus consider the following cases.

- If $\nu > F(1)$, then $\frac{\mathrm{d}SW(q)}{\mathrm{d}q} > 0$ for every q, and the optimal strategy is $q^{soc} = 1$.
- If $\nu < F(0)$, then $\frac{\mathrm{d}SW(q)}{\mathrm{d}q} < 0$ for every q, and the optimal strategy is $q^{soc} = 0$.

Otherwise, there is a unique q' such that $\nu = F(q')$ because of the monotonicity of $F(q)$. It means that $SW(q)$ increases for $q \in [0, q']$ and decreases for $q \in \left(q', 1\right]$. Therefore, $SW(q')$ is the optimal social welfare. This completes our proof. ■

Proof of Theorem 7: For $\nu < F(0)$, the optimal joining probability is $q^* = 0$. By letting $P = C(F(0) - T(0))$, we can obtain the inequality $\frac{R-P}{C} < T(0)$, which is the condition that the equilibrium joining probability is $q^* = 0$. Therefore, $P = C(F(0) - T(0))$ is the optimal price for the social planner corresponding to the socially-optimal joining probability. For $F(1) < \nu$, we can obtain the optimal price similarly.

For $F(0) \le \nu \le F(1)$, the socially-optimal joining probability is $q' \in (0, 1)$. The corresponding optimal price can be obtained from solving $R - P - CT(q') = 0$ uniquely, where $T(q)$ is given in (12). Thus, we can obtain P^*_ser immediately. ■

Proof of Lemma 3: From (66) and (68), we find that the monotonicity of $SW(q)$ is fully determined by $F(q)$, which is increasing in q. We consider three subcases as follows.

- If $\nu > F(1)$, then $\frac{\mathrm{d}SW(q)}{\mathrm{d}q} > 0$ for every q, and the worst service joining strategy can be obtained at $q^\mathrm{w} = 0$.
- If $\nu < F(0)$, then $\frac{\mathrm{d}SW(q)}{\mathrm{d}q} < 0$ for every q, and the worst service joining strategy can be obtained at the largest q. Considering the equilibrium strategy of the users, we have $R - CT(q_\mathrm{e}) \ge 0$. Thus, the equilibrium joining probability is at most q_0. If $q_0 > 1$, i.e., for $\nu > \overline{\nu}$, then the corresponding strategy is $q^\mathrm{w} = 1$. If $0 \le q_0 \le 1$, i.e., for $\nu \le \overline{\nu}$, the worst joining probability is $q_w = q_0$.
- If $F(0) \le \nu \le F(1)$, $SW(q)$ is increasing in $q \in \left[0, q'\right)$ and is decreasing in $q \in \left[q', 1\right]$. Then the worst joining strategy can be obtained at the end points. Thus, if $q_0 > 1$, i.e., for $\nu > \overline{\nu}$, the minimal social welfare is $\min\{SW(0), SW(1)\}$. Otherwise, the minimal social welfare is $\min\{SW(0), SW(q_0)\}$. ■

$$F(q)=\frac{q\lambda(\beta\mu+(1-q)\lambda(\beta+\mu))\left(\frac{\beta^2\theta E[S^2]\mu}{2}+(\beta+\mu)(\theta+\lambda+\beta\rho)\right)}{\beta\theta(\beta\mu-q\lambda(\beta+\mu))^2}+\frac{(\beta\mu+\lambda(\beta+\mu))\left((\beta+\mu)(\beta\mu-q\lambda(\beta+\mu))+\mu\left(\frac{\beta^2\theta E[S^2]\mu}{2}+(\beta+\mu)(\theta+\lambda+\beta\rho)\right)\right)}{\theta\beta\mu(\beta+\mu)(\beta\mu-q\lambda(\beta+\mu))}. \quad (67)$$

$$\frac{\mathrm{d}F(q)}{\mathrm{d}q}=\frac{\lambda\mu(\lambda\mu+\beta(\lambda+\mu)-q\lambda(\beta+\mu))\left(2(\theta+\lambda)\mu+\beta^2(E[S^2]\theta\mu+2\rho)+2\beta(\theta+\lambda+\mu\rho)\right)}{\theta(\beta\mu-q\lambda(\beta+\mu))^3}. \quad (68)$$

B. EQUILIBRIUM RETRIAL RATE

In this part, we consider the case that the retrial rate is endogenously determined by users themselves rather than exogenously given by communication system. Therefore, the trial cost for users should be considered. We denote by C_d and C_t the delay cost per time unit and the trial cost per revisit, respectively. Recall that when all users adopt joining strategy q and retrial rate θ, respectively, the expected waiting time for blocked users is given by

$$T(q)=\frac{1}{\theta}+\frac{\lambda+\rho\beta}{\theta(\beta-\lambda q-\rho q\beta)}+\frac{\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2}}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}.$$

Then the expected number of trials is $\theta\cdot T(q)$ by using Wald's identity (see [1]). And the expected total cost for the blocked users who decide to join is

$$\begin{aligned}\Phi(q,\theta) &= C_dT(q)+C_t\theta T(q)\\ &=\left[\frac{C_d}{\theta}+\frac{C_d(\lambda+\rho\beta)}{\theta(\beta-\lambda q-\rho q\beta)}+\frac{C_d(\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2})}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}\right]\\ &\quad+\left[C_t+\frac{C_t(\lambda+\rho\beta)}{\beta-\lambda q-\rho q\beta}+\frac{C_t\theta(\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2})}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}\right]\\ &=\frac{C_d}{\theta}+\frac{C_d(\lambda+\rho\beta)}{\theta(\beta-\lambda q-\rho q\beta)}+\frac{C_t\theta(\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2})}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}\\ &\quad+\frac{C_d(\lambda+\rho\beta+\frac{\lambda E[S^2]\beta^2}{2})}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}+C_t+\frac{C_t(\lambda+\rho\beta)}{\beta-\lambda q-\rho q\beta}\\ &\geq\frac{2\sqrt{C_dC_t}}{\beta-\lambda q-\rho q\beta}\cdot\sqrt{\frac{[\beta+(\lambda+\rho\beta)(1-q)](\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{\lambda+\rho\beta}}\\ &\quad+\frac{C_d(\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}+C_t+\frac{C_t(\lambda+\rho\beta)}{\beta-\lambda q-\rho q\beta}\end{aligned}$$

where the minimization can be attained at $\hat{\theta}(q)=\sqrt{\frac{[\beta+(\lambda+\rho\beta)(1-q)](\lambda+\rho\beta)}{\lambda+\rho\beta+\lambda E[S^2]\beta^2/2}}$, which decreases in $q\in[0,1]$. By defining $\Psi(q)=\Phi(q,\hat{\theta}(q))$, we have the following lemma.

Lemma 4: $\Psi(q)$ is increasing in $0\leq q<\min\{1,\frac{\beta}{\lambda+\rho\beta}\}$.

Proof: By plugging $\hat{\theta}(q)=\sqrt{\frac{[\beta+(\lambda+\rho\beta)(1-q)](\lambda+\rho\beta)}{\lambda+\rho\beta+\lambda E[S^2]\beta^2/2}}$ into $\Phi(q,\theta)$, we have which can be rewritten as For any $0\leq q<\min\{1,\frac{\beta}{\lambda+\rho\beta}\}$, we have $\beta-\lambda q-\rho q\beta>0$, which decreases in q. And it is not difficult to verify that $\left[\frac{1}{\beta-\lambda q-\rho q\beta}+\frac{\beta+\lambda+\rho\beta}{(\beta-\lambda q-\rho q\beta)^2}\right]$ and $\frac{C_d(\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}+\frac{C_t(\lambda+\rho\beta)}{\beta-\lambda q-\rho q\beta}$ are both increasing in q, which implies that $\Psi(q)$ is increasing in q, this completes the proof. ∎

Lemma 4 shows that the total cost (including trial cost) is increasing in the joining probability, which is intuitive because more negative externalities are resulted when q increases even though the optimal retrial rate is adopted. Next theorem gives the joint equilibrium strategy of blocked users.

Theorem 9: In the IoT system with energy harvesting, a unique Nash equilibrium strategy (q_e,θ_e) of the users observing the IoT device unavailable upon the arrival, i.e., blocked users, to join the waiting orbit exists. The joining probability q_e is given as follows.

For $\lambda<\frac{\mu\beta}{\mu+\beta}$, we have

$$q_e=\begin{cases}0, & \text{if } 0<R-P<\Psi(0),\\ \tilde{q}, & \text{if } \Psi(0)\leq R-P\leq\Psi(1),\\ 1, & \text{if } R-P>\Psi(1),\end{cases} \quad (69)$$

and for $\lambda\geq\frac{\mu\beta}{\mu+\beta}$, we have

$$q_e=\begin{cases}0, & \text{if } 0<R-P<\Psi(0),\\ \tilde{q}, & \text{if } \Psi(0)\leq R-P,\end{cases} \quad (70)$$

where $\tilde{q}$ uniquely solves $\Psi(q)=R-P$. The corresponding equilibrium retrial rate is given by $\theta_e=\sqrt{\frac{[\beta+(\lambda+\rho\beta)(1-q_e)](\lambda+\rho\beta)}{\lambda+\rho\beta+\lambda E[S^2]\beta^2/2}}$.

Proof: Since $\Psi(q)$ is strictly increasing in from Lemma 4, the expected utility $\overline{U}(q)=R-P-\Psi(q)$ is strictly decreasing for q. As we have mentioned before, q_e can characterize an equilibrium if and only if $\arg\min_{\hat{q}\in[0,1]} U(\hat{q};q_e)=q_e$. Notice that when the user who finds a unavailable server chooses to balk, her utility is 0. We can derive the equilibrium q_e by considering the following cases.

1) For the case of $\lambda<\frac{\mu\beta}{\mu+\beta}$, we have the following subcases.
   - When $R-P\in(0,\Psi(0))$, the expected utility for users $\overline{U}(q)$ is negative for every q, i.e., $\overline{U}(q)<0$

$$\Psi(q)=2\sqrt{C_dC_t}\sqrt{\frac{[\beta+(\lambda+\rho\beta)(1-q)](\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)^2}}+\frac{C_d(\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}+C_t+\frac{C_t(\lambda+\rho\beta)}{\beta-\lambda q-\rho q\beta},$$

$$\Psi(q)=2\sqrt{C_dC_t}\sqrt{\frac{\left[\frac{1}{\beta-\lambda q-\rho q\beta}+\frac{\beta+\lambda+\rho\beta}{(\beta-\lambda q-\rho q\beta)^2}\right](\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{\lambda+\rho\beta}}+\frac{C_d(\lambda+\rho\beta+\lambda E[S^2]\beta^2/2)}{(\lambda+\rho\beta)(\beta-\lambda q-\rho q\beta)}+C_t+\frac{C_t(\lambda+\rho\beta)}{\beta-\lambda q-\rho q\beta},$$

for $q\in[0,1]$. Consequently, the best response is not to wait in the orbit, i.e., $\hat{q}=0$, and the unique Nash equilibrium strategy is $q_e=0$.

- When $R-P\in[\Psi(0),\Psi(1)]$, we have $\overline{U}(0)>0$ and $\overline{U}(1)<0$, thus there exists a unique solution $q_e\in(0,1)$ of the equation $\overline{U}(q_e)=0$ because $\overline{U}(q)$ is decreasing in $q\in[0,1]$. In this case, when all other users adopt strategy q_e, we have $\hat{q}U(q_e)=0$ for all $\hat{q}\in[0,1]$, which gives $\hat{q}\overline{U}(q_e)\le q_eU(q_e)$. That is, q_e is the unique Nash equilibrium strategy.
- When $R-P\in(\Psi(1),\infty)$, the expected utility $\overline{U}(1)$ is positive. Therefore, we have $\hat{q}\overline{U}(1)>0$ for any $\hat{q}\in(0,1]$, which implies that joining with probability 1 is the best response for each blocked user, i.e., we have $q_e=1$.

2) For the case of $\lambda\ge\frac{\mu\beta}{\mu+\beta}$, notice that $\lim_{q\to\beta/(\lambda+\rho\beta)}\Psi(q)=\infty$, which implies that $\lim_{q\to\beta/(\lambda+\rho\beta)}\overline{U}(q)=-\infty$. Since $\beta/(\lambda+\rho\beta)<1$, we must have $q_e<1$. Recall that $\overline{U}(q)$ is strictly decreasing in $q\in[0,\beta/(\lambda+\rho\beta))$, we have the following subcases.

- When $R-P\in(0,\Psi(0))$, the expected utility for users $\overline{U}(q)$ is negative for every $q\in(0,\beta/(\lambda+\rho\beta))$, i.e., $\overline{U}(q)<0$ for all $q\in[0,\beta/(\lambda+\rho\beta))$. Consequently, the best response is not to join the orbit, and the unique equilibrium is $q_e=0$.
- When $R-P\in(\Psi(0),\infty)$, we have $\overline{U}(0)<0$ and $\lim_{q\to\beta/(\lambda+\rho\beta)}\overline{U}(q)=-\infty$, thus there exists unique Nash equilibrium $q_e\in(0,\beta/(\lambda+\rho\beta))$ such that $\overline{U}(q_e)=0$ by noticing that $\overline{U}(q)$ is decreasing in $q\in[0,\beta/(\lambda+\rho\beta))$. ■

C. NON-ZERO SETUP TIME

In this subsection, we consider a non-zero setup time to become state 0 (i.e., idle). That is, when the energy harvesting is completed, the IoT device cannot be active until the setup is executed successfully. We assume the setup time is independent and exponentially distributed with rate γ, and define this setup state as $I(t)=3$, then we have four system states as follows:

$$I(t)=\begin{cases}0, & \text{if IoT device is on idle;}\\ 1, & \text{if IoT device is on busy;}\\ 2, & \text{if IoT device is on energy harvesting;}\\ 3, & \text{if IoT device is on setup.}\end{cases}$$

Here we just consider the exponential service time, then the stochastic process of the IoT service $\{(I(t),N(t)),t\ge 0\}$ becomes to a continuous time Markov chain. And the balance equations are expressed as follows:

$$(\lambda+i\theta)p_{0,i}=\gamma p_{3,i}, \tag{71}$$
$$(\gamma+\lambda q)p_{3,i}=\beta p_{2,i}+\lambda q p_{3,i-1}, \tag{72}$$
$$(\beta+\lambda q)p_{2,i}=\lambda q p_{2,i-1}+\mu p_{1,i}, \tag{73}$$
$$(\mu+\lambda q)p_{1,i}=\lambda q p_{1,i-1}+(i+1)\theta p_{0,i+1}+\lambda p_{0,i}, \tag{74}$$

where $p_{i,-1}=0,\ i\ge 0$. Also, we define the following generating functions:

$$\Pi_i(z)=\sum_{j=0}^{\infty}p_{i,j}z^j$$

for $i=0,1,2,3$. By solving these equations, we can have the following theorem.

Theorem 10: For the IoT system with energy harvesting in the steady state, the users enter the waiting orbit with probability q when they find the IoT device unavailable upon the arrival. We have the following results under $\beta\gamma>\rho q(\gamma\mu+\beta\gamma+\mu\beta)$.

1) The probabilities that the IoT device is idle, busy, or harvesting energy are, respectively, given by

$$\Pi_0(1)=\frac{\beta\gamma-\rho q(\gamma\mu+\beta\gamma+\mu\beta)}{\beta\gamma+\rho(1-q)(\gamma\mu+\beta\gamma+\mu\beta)},$$
$$\Pi_1(1)=\frac{\rho\beta\gamma}{\beta\gamma+\rho(1-q)(\gamma\mu+\beta\gamma+\mu\beta)},$$
$$\Pi_2(1)=\frac{\lambda\gamma}{\beta\gamma+\rho(1-q)(\gamma\mu+\beta\gamma+\mu\beta)},$$
$$\Pi_3(1)=\frac{\lambda\beta}{\beta\gamma+\rho(1-q)(\gamma\mu+\beta\gamma+\mu\beta)}.$$

2) The mean numbers of users in the waiting orbit is given in (75), as shown at the top of the next page.

3) The expected waiting time for the repeating users is given in (76), as shown at the top of the next page, which is increasing in q.

Proof: Multiplying equations (71)-(74) by z^i and summing up over all i, we derive the following basic equations after some manipulations, i.e.,

$$\lambda\Pi_0(z)+z\theta\Pi_0'(z)=\gamma\Pi_3(z), \tag{77}$$
$$(\gamma+\lambda q(1-z))\Pi_3(z)=\beta\Pi_2(z), \tag{78}$$
$$(\beta+\lambda q(1-z))\Pi_2(z)=\mu\Pi_1(z), \tag{79}$$
$$(\mu+\lambda q(1-z))\Pi_1(z)=\theta\Pi_0'(z)+\lambda\Pi_0. \tag{80}$$

$$N = \frac{\rho^2\left(q^2(\gamma\mu+\beta(\gamma+\mu))\left(\gamma^2(\theta+\lambda)\mu^2+\beta\gamma(\theta+2\lambda)\mu(\gamma+\mu)+\beta^2\left(\gamma^2(\theta+\lambda)+\gamma(\theta+2\lambda)\mu+(\theta+\lambda)\mu^2\right)\right)\rho\right)}{\beta\gamma\theta(\beta\gamma-q(\gamma\mu+\beta(\gamma+\mu))\rho)((1-q)\gamma\lambda+\beta((1-q)\lambda+\gamma(1+\rho-q\rho)))} + \frac{q\beta\gamma(\gamma\mu+\beta(\gamma+\mu))(\mu(\gamma(2\theta+\lambda)+\theta\mu)+\beta((2\theta+\lambda)\mu+\gamma(\theta+\lambda+\mu)))\rho^3-\beta^2\gamma^2\theta\mu(\beta+\gamma+\mu)\rho^2}{\beta\gamma\theta(\beta\gamma-q(\gamma\mu+\beta(\gamma+\mu))\rho)((1-q)\gamma\lambda+\beta((1-q)\lambda+\gamma(1+\rho-q\rho)))}. \quad (75)$$

$$T(q) = \frac{q\left(\gamma^2(\theta+\lambda)\mu^2+\beta\gamma(\theta+2\lambda)\mu(\gamma+\mu)+\beta^2\left(\gamma^2(\theta+\lambda)+\gamma(\theta+2\lambda)\mu+(\theta+\lambda)\mu^2\right)\right)\rho}{\beta\gamma\theta(\beta\gamma\mu-q\lambda(\gamma\mu+\beta(\gamma+\mu)))} + \frac{(\mu(\gamma(2\theta+\lambda)+\theta\mu)+\beta((2\theta+\lambda)\mu+\gamma(\theta+\lambda+\mu)))\rho}{\theta(\beta\gamma\mu-q\lambda(\gamma\mu+\beta(\gamma+\mu)))} - \frac{\beta\gamma\mu(\beta+\gamma+\mu)}{q(\gamma\mu+\beta(\gamma+\mu))(\beta\gamma\mu-q\lambda(\gamma\mu+\beta(\gamma+\mu)))}. \quad (76)$$

Combining (77)-(80), we have

$$\Pi_0'(z) = \frac{\lambda[\gamma\mu\beta-(\gamma+\lambda q(1-z))(\beta+\lambda q(1-z))(\mu+\lambda q(1-z))]}{[(\gamma+\lambda q(1-z))(\beta+\lambda q(1-z))(\mu+\lambda q(1-z))z-\gamma\mu\beta]\theta} \cdot \Pi_0(z). \quad (81)$$

By letting $z \to 1$, we have

$$\Pi_0'(1) = \frac{\lambda^2 q(\gamma\mu+\beta\gamma+\mu\beta)}{\theta[\beta\gamma\mu-\lambda q(\gamma\mu+\beta\gamma+\mu\beta)]} \cdot \Pi_0(1)$$

through L'Hospital rule. Plugging $\Pi_0'(1)$ into (80) and letting $z = 1$, we have

$$\Pi_1(1) = \frac{\lambda\beta\gamma}{\beta\gamma\mu-\lambda q(\gamma\mu+\beta\gamma+\mu\beta)} \cdot \Pi_0(1). \quad (82)$$

By substituting (82) into (79) and letting $z = 1$, it gives

$$\Pi_2(1) = \frac{\lambda\mu\gamma}{\beta\gamma\mu-\lambda q(\gamma\mu+\beta\gamma+\mu\beta)} \cdot \Pi_0(1). \quad (83)$$

Similarly, by plugging (84) into (78), we can get

$$\Pi_3(1) = \frac{\lambda\mu\beta}{\beta\gamma\mu-\lambda q(\gamma\mu+\beta\gamma+\mu\beta)} \cdot \Pi_0(1). \quad (84)$$

Based on the normalization condition that $\sum_{i=0}^{3}\Pi_i(1) = 1$, we can derive $\Pi_i(1)$ for $i = 0, 1, 2, 3$. By taking the deviation of (80) and (81) with respect to z, and letting $z = 1$, we have

$$(\lambda+\theta)\Pi_0'(1)+\theta\Pi_0''(1) = \gamma\Pi_3'(1), \quad (85)$$

$$\Pi_0''(1) = \frac{\lambda^3 q^2\left[(\lambda+\theta)(\gamma\mu+\beta\gamma+\beta\mu)^2-\theta\beta\gamma\mu(\beta+\gamma+\mu)\right]}{[\beta\gamma\mu-q\lambda(\gamma\mu+\beta\gamma+\beta\mu)]^2\theta^2} \times\Pi_0(1). \quad (86)$$

Taking the deviation of the both sides for (78), (79), and letting $z = 1$, we can get

$$\gamma\Pi_3'(1)-\lambda\Pi_3(1) = \beta\Pi_2'(1), \quad (87)$$

$$\beta\Pi_2'(1)-\lambda\Pi_2(1) = \mu\Pi_1'(1). \quad (88)$$

By solving the equations (85)-(88), we can get

$$\Pi_1'(1) = \frac{\theta\Pi_0''(1)-\lambda(\Pi_2(1)+\Pi_3(1))+(\theta+\lambda)\Pi_0'(1)}{\mu}$$

$$\Pi_2'(1) = \frac{\theta\Pi_0''(1)-\lambda\Pi_3(1)+(\theta+\lambda)\Pi_0'(1)}{\beta}$$

$$\Pi_3'(1) = \frac{\theta\Pi_0''(1)+(\theta+\lambda)\Pi_0'(1)}{\gamma}$$

By plugging $\Pi_0'(1)$ and $\Pi_0''(1)$ into the equations above, we can derive $\Pi_1'(1)$, $\Pi_2'(1)$ and $\Pi_3'(1)$, respectively. Then the total mean number of users in orbit can be obtained as $N = \sum_{i=0}^{3}\Pi_i'(1)$. And the mean delay for blocked users is given by $T(q) = N/(\lambda[1-\Pi_0(1)])$ by using Little's formula. It is noted that

$$\frac{d^2\,T(q)}{dq^2} = -\frac{2\beta\gamma\mu(\beta+\gamma+\mu)(\beta\gamma\mu-q\lambda[\gamma\mu+\beta(\gamma+\mu)])}{q^3(\gamma\mu+\beta(\gamma+\mu))} < 0.$$

Thus we have that $\frac{dT(q)}{dq}$ is decreasing in q. Because we have that $q < \frac{\beta\gamma\mu}{\lambda(\gamma\mu+\beta\gamma+\beta\mu)}$, by plugging $q = \bar{q} = \frac{\beta\gamma\mu}{\lambda(\gamma\mu+\beta\gamma+\beta\mu)}$ into $\frac{dT(q)}{dq}$, it is not difficult to verify that $\frac{dT(q)}{dq}|_{q=\bar{q}} > 0$. Therefore, we can get that $T(q)$ is increasing in q, which completes this proof. ■

Remark: Theorem 10 derives the system performance measures of IoT system when the setup time is considered. In this case, we can observe that all the steady-state probability of idle $\Pi_0(1)$ is smaller than that in Theorem 1 in the presence of setup time. That is, there is a larger probability for users to be blocked upon arrival. In particular, when $\gamma \to \infty$, the setup time approaches to 0, and the $\Pi_3(1)$ approaches to 0, too. Also, it is not difficult to verify that the steady-state probabilities $\Pi_0(1)$, $\Pi_1(1)$ and $\Pi_2(1)$ degenerate to that in Theorem 1. Notice that the mean delay of blocked users is increasing in q, which implies that the expected utility for blocked users who decide to join is decreasing in q. Thus a unique equilibrium joining strategy can be characterized by using the similar argument in Theorem 2.

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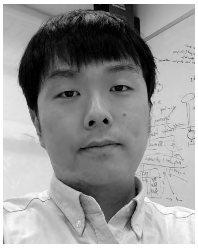

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