electronics

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# Mobile-Based Sensing Scheme to Minimize Battery Power Consumption for Urban Monitoring Systems

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**Abstract:** In urban monitoring systems, mobile sensing is imperative to acquire data from sensors and relay them to a cloud server. Mobile devices can be used anytime and anywhere, enabling communication with pervasive sensing in various conditions to obtain the data. Reliable data acquisition has been required in urban monitoring systems from the macroscale to the microscale. However, a broadcast method for the data acquisition process may lead to the increased battery power consumption of mobile devices. Managing the battery power consumption of mobile devices is essential for reliable data acquisition. In this paper, we propose an urban monitoring system with an optimization algorithm in which a cloud server broadcasts a communication request that includes battery power consumption and the data acquisition quantity of mobile devices. Game theoretic optimization is formulated with a decision process. We derive a best response and Nash equilibrium for mobile communication with sensors and a cloud server. Evaluation results demonstrate that the proposed system can guarantee a low battery power consumption, as well as acquire the desired data quantity.

**Keywords:** mobile sensing; energy efficiency; game theoretic optimization



**Citation:** Lee, S.-H.; Yang, T.; Kim, T.-S. Mobile-Based Sensing Scheme to Minimize Battery Power Consumption for Urban Monitoring Systems. *Electronics* **2021**, *10*, 198. https://doi.org/10.3390/electronics10020198

Received: 30 November 2020
Accepted: 12 January 2021
Published: 16 January 2021



## 1. Introduction

In urban systems for a smart city using Wireless Sensor Network (WSN) technologies, real-time environment monitoring is essential to provide helpful information that can be used for urban management [1]. To acquire data from multiple sensors deployed on urban monitoring systems, sensing technologies such as Bluetooth and radio-frequency identification are essential [2]. In addition, WSN-based sensing communication has been developed rapidly and applied in many areas [3]. Users with mobile devices (e.g., smart phones, smart watches, and smart tablets) are connected to a WSN, and many static sensors are sparsely deployed in the urban systems [4]. Mobile devices are used to relay the data from sensors to a cloud server and should satisfy event reliability such that the quantity of sensing data is large enough to be utilized [5]. Furthermore, reliable data acquisition at numerous urban monitoring places from the macroscale to the microscale has been required. In urban monitoring systems with a WSN, a large number of scattered sensors conduct sensing tasks and multihop networking over a temporarily configured ad hoc network. To communicate with sensors and relay the data to the cloud server, it is important to maintain the battery power of mobile devices [6]. Although the battery power efficiency of mobile devices has increased, people spend more time and use more data via their mobile devices than ever before [7]. As mobile device users have increased along with data-heavy mobile applications, the overall battery power consumption of mobile devices has also increased [8]. Therefore, mobile devices must maintain their battery power above a certain level to communicate with sensors and the cloud server in urban systems. Here, it is challenging for mobile devices to determine the communication with sensors and the cloud server.

Currently, air quality is one of the essential real-time monitored indexes in urban systems (e.g., particulate matter, oxide gases, carbon monoxide, etc.), and many countries have deployed urban sensing and monitoring infrastructure to provide useful information to their citizen [9]. In the urban-scale monitoring infrastructure, each sensor measures the air quality, weather, and noise parameters sent to a cloud server using mobile devices [10]. However, few sensors are deployed in urban systems so that their data show rough information. Furthermore, mobile devices cannot acquire data in some environments (e.g., not enough battery power for mobile devices, users in vehicles).

In this paper, we propose a data acquisition system with the optimization of the battery power consumption of each mobile device. After receiving the cloud server request, each mobile device accepts the request and conducts the data acquisition considering its battery power consumption. The game theory model is formulated to minimize battery power consumption while acquiring more data than the desired level. Furthermore, a Nash equilibrium is derived via the best response strategy algorithm. To evaluate our system, we implement Particulate Matter (PM) sensors to monitor air quality. PM sensors are deployed in various environments, sending the data to mobile devices. The contributions of this paper can be summarized as follows: (1) we model the minimization of the battery power consumption in mobile devices and optimize the model; (2) based on a game theoretic method, we derive the optimal strategy, which implies that the strategy can be adopted by the real urban system; and (3) we present and analyze the evaluation results under various environments. Experimental results show that the proposed system acquires more data than the data acquisition threshold and consumes less battery power than the target battery power status.

The remainder of this paper is organized as follows. In Section 2, we summarize the related work. In Section 3, we elaborate on the system model. In Section 4, we formulate the system model as a game theoretic process. The optimization for the game theoretic process is described in Section 5. Evaluation results are discussed in Section 6, and our concluding remarks are provided in Section 7.

## 2. Related Work

Studies on urban sensing to acquire microscale data have been reported in the literature [11–13]. The authors in [11] utilized geotagged tweets, sensing data for urban temperature analysis, and investigated the relationships between monitored temperatures and heat-tweets using a statistical model based on copula modeling methods. In [12], an integrated geovisualization framework was proposed. This framework was used to analyze the complex patterns of an urban microclimate for real-time wireless sensor network data. In the proposed algorithm, a Bayesian method and a hyper ellipsoidal model were used to analyze the data in the urban microclimate, as well as a smart city environment. The authors in [13] suggested a decentralized data fusion framework. The proposed framework was utilized for microscale monitoring systems in urban monitoring environments using a sensor network. Furthermore, an urban air pollution monitoring scenario demonstrated the proposed framework.

Data relaying using mobile devices was utilized in [14–16]. In [14], the authors proposed a hybrid protocol for delivering data from sensors to mobile devices and analyzed the performance of the protocol to derive the probability model of the data delivery. Then, the authors derived the performance of the parameters and the effectiveness of the model. In [15], the authors presented a mobile-cloud middleware for opportunistic mobile sensing using smart phones. This middleware allows dynamically downloading and installing sensor-specific transcoding modules using the mobile device as the sensor type. The authors in [16] modeled data pre-forwarding as an optimization problem to improve the performance of opportunistic data collection with smartphones. Then, a formal network model and a mechanism for data pre-forwarding were proposed, and the optimal solution was derived. Finally, the authors evaluated a small laboratory testbed with scenarios based on smartphone users.

Optimization problems for energy consumption have been proposed [6–8]. In [6], the authors proposed adaptive scheduling algorithms to enhance the energy efficiency of mobile devices in cellular networks considering user performance. The authors designed an algorithm to minimize the total energy cost for data transfers subject to mobile user performance constraints. The hybrid energy optimization was formulated and demonstrated to validate the energy efficiency of the proposed algorithm. The authors in [7] examined the trends of the energy power consumption of mobile devices for data transfer and mobile networks based on a top-down energy intensity estimate and public data. Energy consumption for mobile data transfer was analyzed from the perspective of the life cycle, examining both direct and indirect energy use. The authors in [8] proposed a service-specific and end-to-end energy consumption model to investigate smartphone applications and conducted a sensitivity analysis on different usage patterns. Furthermore, the authors suggested energy-efficient solutions to reduce the service energy consumption.

In spite of the above issues, there is no existing work that optimizes the overall battery power consumption of mobile devices in a mobile-based sensing scheme. In [5], the authors proposed a reliable event data acquisition system for mobile-assisted urban monitoring named urban reliable event transport (uRET). uRET was designed for reliable event transmission from sensors to a cloud server using mobile devices. The authors in [5] showed that uRET can provide a high delivery success ratio and event reliability accomplishment ratio in a dynamic environment. However, this work did not consider the battery power consumption of mobile devices. Our work aims to optimize the battery power consumption of mobile devices while satisfying the data acquisition threshold. We propose a novel energy-efficient data collection model for mobile devices based on the users' battery status and duration.

## 3. Model Description

Figure 1 shows the proposed urban monitoring system. There are many people using mobile devices such as smartphones, smart watches, smart tablets, and so on. Each mobile device in the system communicates with sensors that consist of a PM sensor with a Bluetooth chip-set. Mobile devices in the urban monitoring system consume power when transferring the data to the cloud. Therefore, urban monitoring communication can be disrupted by the remaining battery status of mobile devices. The system should consider the battery power consumption of mobile devices to guarantee event reliability. When the cloud server receives the data and information of mobile devices, it supervises all the procedures to get the required event reliability. The cloud server utilizes Algorithm 1. Sensors in the urban monitoring system consist of the sensing and communication modules and broadcast the Bluetooth signals. Then, all the mobile devices in the event area send the data of the sensors and their battery power status to the cloud. The cloud analyzes the information of the mobile devices and performs the algorithm to acquire reliable data transmission to satisfy the data threshold. After receiving the request to determine which mobile device sends the data to the cloud, the mobile devices send the data to the sensors within a time duration to achieve the threshold for data acquisition.

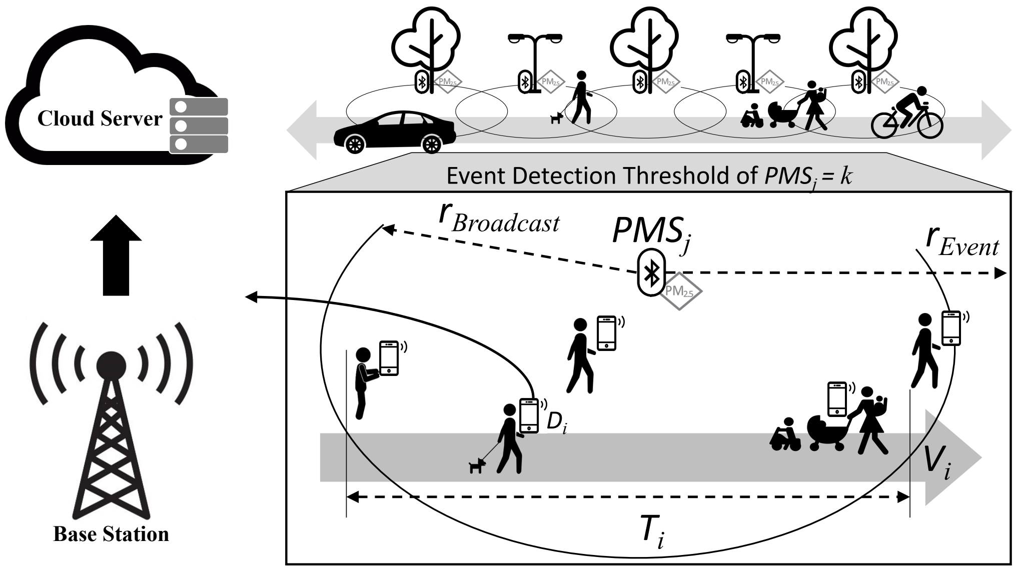


**Figure 1.** PM monitoring.

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**Algorithm 1:** Optimization algorithm.

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$T_{acq} = TIME\_DATA\_ACQUISITION$
**while** $T_{acq} \neq 0$ **do**
  $D = Devices\_Set\_Around\_PMS_j$
  **for** $D_i$ *in* $D$ **do**
    $E_i = getBatteryPowerStatus(D_i)$
    $V_i = getMovingVelocity(D_i)$
    $T_{stay} = getStayTime(V_i)$
    $S_i = calculateBestResponseStrategy(E_i, T_{stay})$
    $List.add(D_i, S_i)$
  **end**
  $D^* = NashEquilibrium(List)$
  **for** $[D_i, S_i]$ *in* $D^*$ **do**
    $sendCommandToDevice(D_i, S_i)$
  **end**
**end**

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## 4. Game Theoretic Formulation

In this section, we formulate a game model to achieve a decision process for the reliable data acquisition system. The game model is composed of a set of players, a set of strategies used by a player, and a payoff for each strategy [17]. Note that, because the mobile devices are the players in the game model, the terms player $i$ and mobile device $D_i$ are used interchangeably. The important notations for the game model are summarized in Table 1.

**Table 1.** Summary of notations.

| Notation | Description |
|---|---|
| $i$ | Player $i$ |
| $D$ | A set of mobile devices |
| $D_i$ | Mobile device of player $i$ |
| $D_{-i}$ | Mobile devices of all players except player $i$ |
| $PMS_j$ | PM sensor $j$ |
| $V_i$ | Velocity of $D_i$ within $PMS_j$ |
| $T_i$ | Time duration of $D_i$ staying within $PMS_j$ |
| $N_j$ | Received data from $PMS_j$ |
| $S$ | A set of strategies |
| $S_i$ | Strategy of player $i$ |
| $p_i$ | Probability of the data loss rate between mobile device $D_i$ and $PMS_i$ |
| $E_i$ | Initial battery status of mobile device $D_i$ |
| $E_t$ | Battery power consumption during $T_i$ |
| $E_r$ | Total remaining battery power of mobile device $D_i$ |

### 4.1. Player

Mobile device $D_i$ is a player in the game model, where $i = \{1, 2, \ldots, n\}$. $D$ is a set of mobile devices $D_i$ denoted as $D = \{D_1, D_2, \ldots, D_i\}$. In addition, $D_{-i}$ represents all players except player $D_i$. In the PM monitoring system, $D_i$ stays in the event area denoted by $T_i$ with moving velocity $V_i$. Mobile device $D_i$ receives the number of data denoted by $N_j$ from $PMS_j$, where $PMS_j$ denotes PM sensor $j$. Let $p_i$ denote the probability of the data loss ratio between mobile device $D_i$ and PM sensor $PMS_j$. After receiving the data from $PMS_j$, mobile device $D_i$ sends the data to the cloud server. We assume that mobile device $D_i$ sends all the acquired data to the cloud server. Therefore, the quantity of acquired data from PM sensor $PMS_j$ during $T_i$ is given by:

$$D_{acq}(i) = N_j \cdot T_i \cdot (1 - P_i), \tag{1}$$

Furthermore, $E_i$ represents the initial battery power status of mobile device $D_i$, which the cloud receives at first. When mobile device $D_i$ accepts the request from the cloud server during $T_i$, it consumes its battery power $E_t$ to send the data to the cloud server received from sensor $PMS_j$. Hence, the total remaining battery power of mobile device $D_i$ during $T_i$ is defined as follows:

$$E_r = E_i - E_t \cdot T_i. \tag{2}$$

### 4.2. Strategy

$S_i$ is a strategy of player $i$. $S_i$ can be represented as $S_i = \{0, 1\}$, where $S_i = 0$ means that mobile device $D_i$ does not accept the connection of PM sensor $PMS_j$'s request, whereas $S_i = 1$ indicates that mobile device $D_i$ accepts the connection of PM sensor $PMS_j$'s request. Then, a set of strategies $S$ can be denoted by $S = \{S_1, S_2, \ldots, S_i\}$.

### 4.3. Payoff Function

To maintain a battery power consumption below a certain level during the data acquisition, we define the battery power consumption function as $E(D_i, S_i)$. If mobile device $D_i$ accepts the request from the cloud server (i.e., $S_i$ = 1), it consumes battery power $E_t$ during $T_i$.

$$E(D_i, S_i) = \begin{cases} E_t \cdot T_i, & if\ S_i = 1 \\ 0, & if\ S_i = 0 \end{cases}, \tag{3}$$

Each mobile device $D_i$ chooses its strategy $S_i$ to acquire the data threshold. We define a payoff function as $\pi(D_i, S_i)$. This function represents the total acquisition data of mobile device $D_i$. If mobile device $D_i$ receives the request and accepts it (i.e., $S_i = 1$), the sensor-mobile communication between $D_i$ and $PMS_j$ is processed with probability $1 - p_i$. After receiving data $N_j$ from $PMS_j$ in its staying time $T_i$, mobile device $D_i$ transmits the data to the cloud. Therefore, $\pi(D_i, S_i)$ can be represented by Equation (4).

$$\pi(D_i, S_i) = \begin{cases} N_j \cdot T_i \cdot (1 - p_i), & if\ S_i = 1 \\ 0, & if\ S_i = 0 \end{cases}. \tag{4}$$

## 5. Optimization Formulation

### 5.1. Optimization Algorithm

The procedure of Algorithm 1 is as follows. First, each mobile device $D_i$ initializes its strategy $S_i$ and communicates with $PMS_j$. Mobile devices send the battery power status $E_i$ and moving velocity $V_i$ to the cloud server. After receiving the information of all the mobile devices $D$, the cloud server calculates the best response strategy and Nash equilibrium including the data acquisition quantity of each mobile device $D_i$ during $T_i$. Finally, the cloud sends the request to all mobile devices $D$ for strategy $S_i$. After that, the cloud solves the linear programming to obtain the optimization problem and derive a solution for minimizing the battery power consumption. This procedure is repeated every time period until having acquired more data than threshold $K$. Note that the proposed algorithm can determine the optimal strategy within a few time periods, which means that it can be implemented without a high overhead load on the cloud.

### 5.2. Best Response and Nash Equilibrium

We consider a Nash equilibrium as a solution of the game for the battery power consumption optimization and the data acquisition problem. The Nash equilibrium exists for the game, and it is unique. Furthermore, the best response strategy is used to derive the Nash equilibrium [18]. The strategy $s^* = (s_n^*, s_{-n}^*)$ is the best response strategy if $p_i(s_n^*, s_{-n}^*) \geq p_i(s_n, s_{-n})$ for each player $i$. If the set of strategies is a Nash equilibrium of the game, then no player changes its strategy. A Nash equilibrium $s_i^*$ of player $i$ can be defined as follows:

$$p_i(s_n^*, s_{-n}) \geq p_i(s_n, s_{-n}), \tag{5}$$

### 5.3. Optimization Model

To minimize the total battery power consumption, we formulate an optimization problem as a linear programming model. We assume that the optimization is conducted every time, and thus, we consider the one time model as follows:

$$\min \quad \sum_{i=1}^{n} E(D_i, S_i), \tag{6}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} \pi(D_i, S_i) > K, \tag{7}$$

$$E_i > \theta, \tag{8}$$

The Nash equilibrium is the optimal strategy for which the mobile device communicates with a sensor. When mobile device $D_i$ accepts the request, it communicates with a sensor in the time duration. The objective function in Equation (6) is designed to minimize the total battery power consumption of the mobile devices. Furthermore, the constraint in Equation (7) is employed to maintain the acquisition of more data than the target threshold $K$. The constraint in Equation (8) represents the remaining battery power status of each mobile device satisfying more than the target battery power $\theta$.

## 6. Performance Evaluation

### 6.1. Preliminary Experiments for the Bluetooth Low Energy Beacon

This section explains the performance evaluation via a proof of concept with Bluetooth and laser particulate matter (PM2007) sensors on the Arduino Due platform and ten mobile devices with iOS Version 12.2 and Android OS Version 7.0. The optimization analytics relying on game theory was implemented on a Linux Ubuntu 16.04 LTS with Django 2.1. We examined various environments: a school, the roadside, a market, and a park. We located the sensors along a street. Then, we collected 8000 values as the data. Furthermore, we investigated the environmental properties of the Bluetooth Low Energy (BLE)-based interaction between the mobile devices and the sensors since the BLE advertisement and the receiving ratio at mobile devices suffer from environmental situations like the height of the BLE transmitter, the distance between the mobile devices and sensors, and the moving speed of users.

Figure 2 shows the effect of the signal strength on the transmission distance under the user's different moving speeds at 3.6 km/h and 10 km/h, respectively. The distance between the mobile device and the sensor was measured at 10 m, 20 m, and 30 m, respectively. With the increase of the distance between the mobile device and sensor, the signal strength decreased. In our model, we did not consider the distance between mobile devices and sensors. That is, the communication was not disrupted by the distance (e.g., the distance between mobile devices and sensors was less than 30 m). In addition, the signal strength decreased as the moving speed increased. In this result, we assumed that the user's moving speed in the urban monitoring system affects the communication between mobile devices and sensors. If the moving speed of the mobile device is faster than a certain level, the probability of data loss ratio between mobile devices and sensors is much higher. Figure 3 shows the signal strength according to the height of the sensor at 0 m and 2 m, respectively, and the distance between the sensor and mobile device was measured at 10 m, 20 m, and 30 m, respectively. This figure shows that the higher the height of the sensor, the stronger the signal is. It can be observed that the sensor should be deployed on the wall rather than on the ground. Therefore, we deployed the sensor on the wall for the experiments. Figure 4 shows the average reception ratio for a transmission distance between 0 m and 40 m. In this graph, with the increase of the distance between the sensor and mobile device, the average reception ratio decreases. Figure 5 shows the average times of the scan interval according to the angle of the beacon.

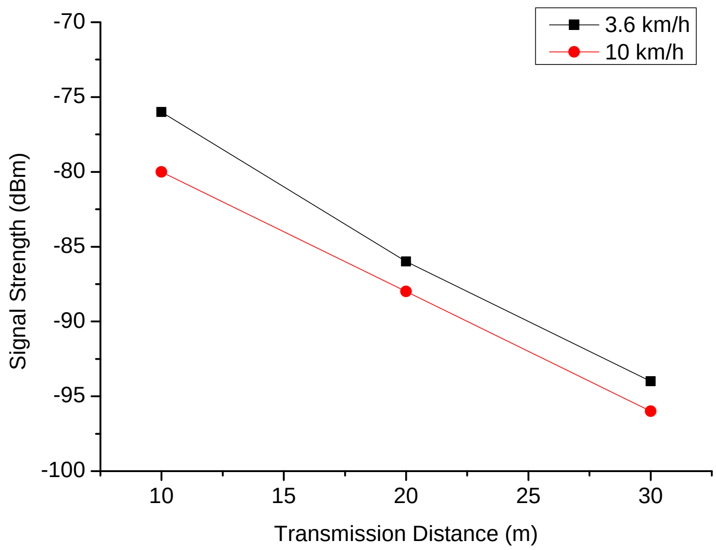


**Figure 2.** Signal strength for the moving speed.

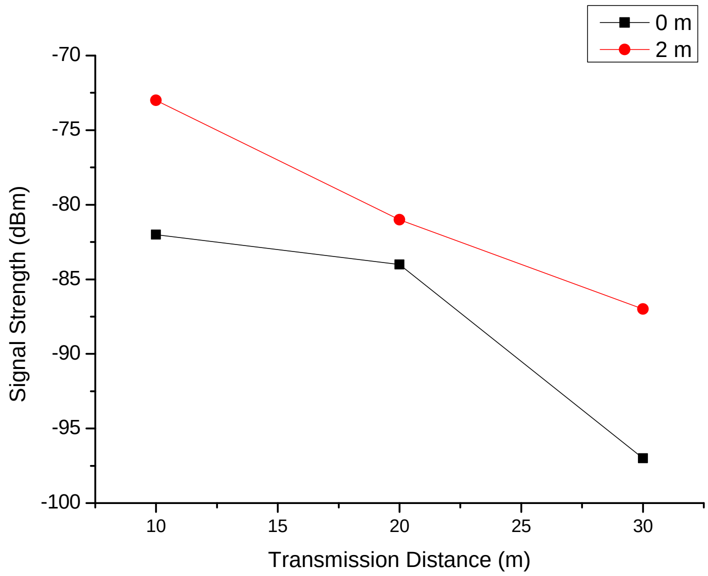


**Figure 3.** Signal strength for the height of the sensor.

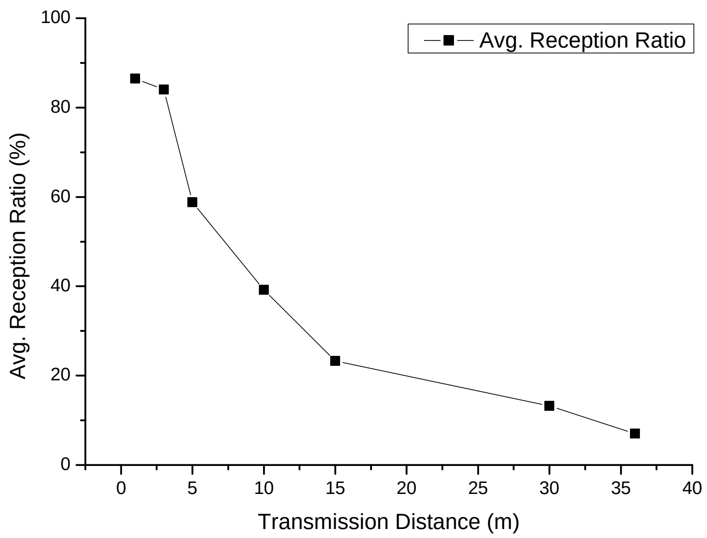


**Figure 4.** Average of reception ratio for the transmission distance.

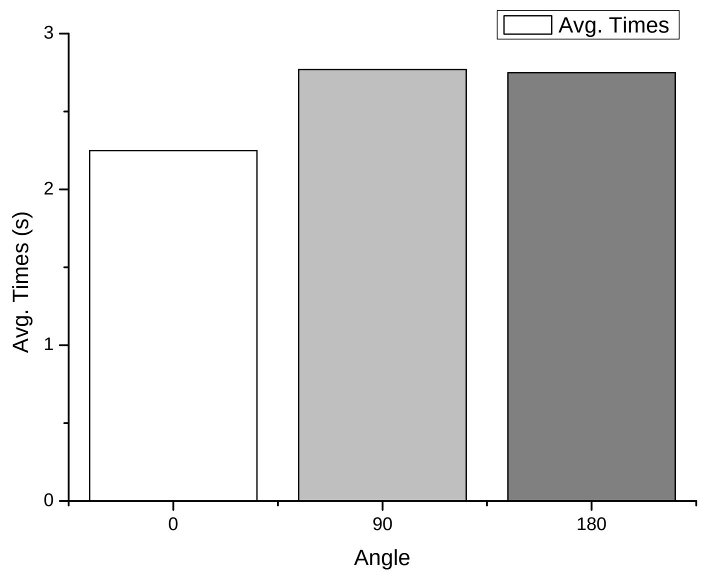


**Figure 5.** Scan interval times for the approach angle.

### 6.2. Battery Power Minimization Model

For the performance evaluation of the proposed system, we compared the optimization with uRET-Broadcast [5]. The scenario is as follows: The number of mobile devices that can receive requests was set to 10. Three $PMS_j$ were deployed and installed every 25 m. The data acquisition threshold $K$ and target battery power of each mobile device $\theta$ were 60 and 50%, respectively. In Figure 6, we show the quantity of data acquisition for the time period. There are two data acquisition graphs: one is the proposed game theoretic optimization approach, and the other is uRET-Broadcast. The game theory-based approach shows the convergence to the data acquisition threshold after getting the Nash equilibrium in 7 s. However, uRET-Broadcast shows that the data acquisition increases as the time period increases, because there is no optimization constraint on this model. However, the convergence time of uRET-Broadcast is faster than the proposed model. This is because all mobile devices on uRET-Broadcast send the data to the cloud server while they stay in the event area of the sensors. Figure 7 shows the average remaining battery power in each time period. There are ten mobile devices with an average battery capacity of 71%. It can be seen that the average remaining battery power of the proposed model decreases by 7 s to acquire the target data quantity, the same as in Figure 7. After converging to the target data threshold, the battery power consumption of the proposed model decreases slowly. On the contrary, the average remaining battery power of the uRET-Broadcast model keeps decreasing. Figure 8 shows the required time for data acquisition in each iteration. It shows that the proposed model requires more time than the uRET-Broadcast model for every iteration. This is because the remaining battery power of mobile devices below 50% is not included in the data acquisition procedure. Although the proposed model requires more time duration, it acquires the data within a few seconds, as well as minimizes the battery power consumption of the mobile devices.

Our results show that the game theory-based model converges to the Nash equilibrium within a few seconds (i.e., average of 7.6 s in Figure 8). This observation demonstrates that the proposed model can be applied to real urban systems without high overhead for calculating on the cloud. However, if many mobile devices have their battery status under the target battery power in urban systems, the proposed model could not satisfy the data threshold. This means that the proposed model has the advantage of satisfying the data acquisition and the battery power consumption when there are many mobile devices in the system.

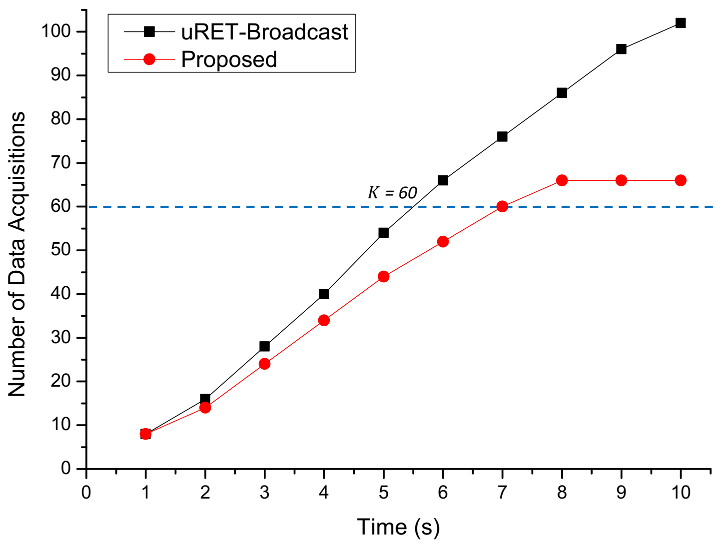


**Figure 6.** Number of data acquisitions.

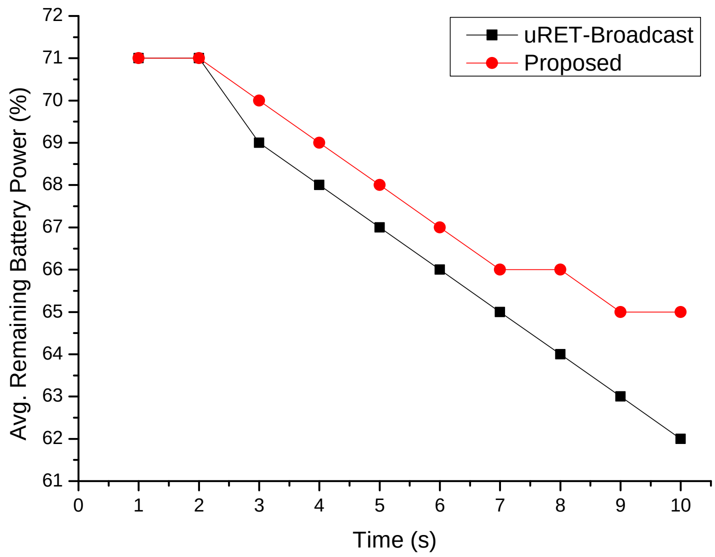


**Figure 7.** Avg. remaining battery power.

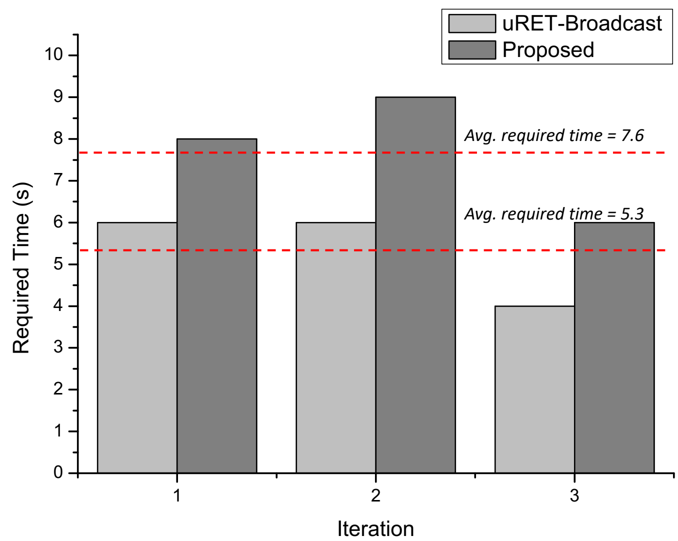


**Figure 8.** Required time.

## 7. Conclusions

In this paper, the battery power issue for PM monitoring in an urban system is addressed. We design a game theoretic optimization problem for the battery power consumption of mobile devices. Mobile devices and PM sensors on the embedded system are implemented in various environments. In the proposed system, the cloud server performs the optimization algorithm and sends the request to the mobile devices. Furthermore, the mobile devices accept the optimal strategy derived from the cloud server via the best response dynamics and Nash equilibrium. The performance evaluation results demonstrate that mobile devices in the proposed system accept the request and thus acquire more data than the threshold, and a low battery power consumption can be guaranteed. In future work, we will consider more scenarios such as multiple sensors in urban systems and the dynamic mobility of users. In sensor-mobile communication, not only broadcast mode, but also unicast mode will be considered. Furthermore, to achieve a high reliability for the data acquisition, additional constraints will be adopted in the game theory model.

**Author Contributions:** S.-H.L. and T.-S.K. conceived of the idea of this research; S.-H.L. and T.Y. performed the experiments and simulation; S.-H.L., T.Y. and T.-S.K. analyzed the experimental data and wrote the article. All authors read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest.

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