Resource Allocation in Wireless Powered Virtualized Sensor Networks

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ABSTRACT

As an important technology for Internet of Things, wireless sensor networks have been receiving widespread attention in recent years. Traditional wireless sensor network deploys resources for specific applications, which causes the problem of low resource utilization. Additionally, the energy consumption brought by the diversification of application requirements has also raised the burden on sensor nodes. Therefore, based on the introduction of wireless energy transfer technology, this paper proposes a resource allocation strategy for virtualized wireless sensor networks. Specifically, physical resources are pooled by the the wireless sensor network service provider. Then, virtual sensor networks are built through network slicing technology to provide one-to-one services based on the application requirements and the current status of the physical sensor nodes. Furthermore, in order to minimize the overall network energy consumption, a system-friendly resource allocation strategy is proposed to optimize the jointly configurations of sensing frequency, time slot and transmission power. Simulation results validate that the proposed strategy can not only effectively save the network energy, but also meet the diverse personalized needs of applications.

INDEX TERMS

Wireless sensor network, virtualization, wireless energy transfer, resource allocation.

I. INTRODUCTION

With the technology enhancements in Internet of Things, including sensing [1], communication [2], computation [3] and caching [4], the application field of wireless sensor networks (WSNs) has gradually developed from military [5] to precision agriculture [6], smart health [7], intelligent transportation [8] and etc, which plays a more and more important role in human’s daily life. Usually, the deployment of sensor nodes is task oriented. Due to the discontinuous occupation of node resources by a single specific task, WSN suffers the problem of low resource utilization. For example, the residents and governments deploy similar sensor nodes to monitor the temperature individually in the same area. Such redundant deployment of infrastructure may result in unnecessary financial waste.

Generally, sensor nodes are usually powered by batteries or other embedded energy sources. However, such nodes may be deployed on a large scale in toxic areas, structures of building or inside the human body [9]. Hence, it is difficult to replace the battery when energy is exhausted. How to break through the performance bottleneck caused by energy limitation consequently becomes a hot research topic. In order to prolong life of sensor nodes, there are two types of means which are “throttling” and “open source”. “Throttling” refers to reducing energy consumption or improving energy efficiency through some reasonable optimization schemes. In particular, similar with the traditionally Internet that needs to support various types of applications [10], [11], WSN can also apply virtualization technology to improve its resource utilization. Specifically, the applications with different performance requirements can be operated transparently by virtual sensor nodes that are centrally managed by a WSN service provider [12]. Differently from “throttling”, “open source” prolongs the sensor life via wireless energy transfer.
transfer (WET) technologies, such as inductive coupling, magnetic resonance coupling and electromagnetic wave radiation [13]–[15]. The “throttling” based and “open source” based approaches have brought performance improvement to some degree for the current WSN. However, in the coming era of Internet of Everything [16], the ever-increasing applications may bring heavier load and much higher performance requirements to the WSN. In this case, “throttling” and “open source” may not be effective any longer if they are applied individually. Consequently, combining such two approaches together becomes a good choice to break through the bottleneck of the current WSN.

Motivated by this, this paper studies a resource allocation strategy to meet the performance requirements of multiple concurrent applications in a WSN. Particularly, wireless charging technology is introduced to compensate the network energy consumption. Specifically, the architecture of the virtualized WSN and the communication model of nodes are constructed with consideration of concurrent requests of different applications. Then the virtual sensor networks (VSNs) corresponding to different applications are formed through jointly optimizing the data sensing frequency, the energy harvesting and data transmission time, and the transmission power of the sensor nodes. The analysis and results, explicitly revealing the impacts of wireless charging power and application data volume on the energy consumption of WSN, shed new light for the design of a rechargeable virtualized WSN.

The main contributions of this paper are as follows:

- A three-layer architecture for virtualized WSN is proposed. Under this architecture, resources of physical sensor nodes are pooled and centrally scheduled by a central controller. Therefore, the resources of the node can serve multiple applications at the same time, which improves the manageability of WSN and the utilization of underlying resources.

- The gain of wireless charging to a WSN is analyzed, which can provide a guideline to a practical WSN to adjust the charging power adaptively according to the application demands.

- The “throttling” idea and “open source” idea are combined in this paper to deal with the concurrent requests of multiple applications. Particularly, a resource allocation strategy is obtained to optimize the jointly configurations of the sensing frequency, energy charging power and data transmission time as well as transmission power. Moreover, the proposed strategy provides a fair resource competition environment among different applications.

The remaining of this paper is organized as follows. Section II introduces the related works. Section III proposes a virtualized WSN model and communication model with WET. The resource optimization problem is formulated in Section IV and the resource allocation strategy is obtained in Section V. In Section VI, simulation results are presented and discussed. Section VII finally concludes the paper.

II. RELATED WORK

As a long-term focus of attention, there have been amounts of researches on WSN energy consumption based on single-layer or cross-layer optimization.

The single-layer researches includes intelligent task allocation and redundant scheduling at the application layer, efficient routing and low-power routing at the network layer, node sleep and beamforming at the physical layer, etc. Detailed surveys are as follows. In [17], the author proposed a binary particle swarm optimization algorithm to achieve the balance between the energy consumption and time needed to complete a assigned task by the sensor node. This strategy enabled WSN to adapt to the expansion of the network scale while saving energy. Kim et al. proposed a lightweight load balancing mechanism for the congestion problem of WSN based on the RPL protocol, which allowed each sensor node to select a parent node in terms of the queue utilization of its neighbor nodes and the number of hops required to the border router [18]. With the proposed scheme, the packet loss probability of WSN was reduced. In [19], imbalanced energy consumption among nodes in a rechargeable WSN was studied where an overlay learning scheduling algorithm based on reinforcement learning was proposed. The algorithm instructed the nodes to perceive the environment and adjusted the working mode according to the priority operator, residual energy and charging frequency. However the above works [17]–[19] just focused on single layer, which only yields local energy benefits and may bring conflict to other layers in a WSN.

Cross-layer researches includes the design of new architectures, the joint optimization of transmission power and coding, the joint optimization of application access and resource allocation, and etc. Details are summarized as follows. A software defined WSN architecture was brought up in [20], dividing the control module into fast changing module and slow changing module. It implemented centralized resource scheduling to reduce congestion and achieve fair allocation of user. Wolf et al. used distributed source coding for WSN based on the correlation between perceptual data to improve energy efficiency, and proposed an effective energy allocation scheme to enhance system performance [21]. In [22], the author focused on how to manage the underlying physical resources with objective to maximize the number of application deployments in a shared WSN. However, these existing cross-layer optimization strategies ignored the characteristics of WSN and thus had certain shortcomings in flexibility.

In order to further enhance the resource utilization and prolong the network life cycle for the WSN, virtualization technology was introduced in [23]. The WSN therein was divided into node-level virtualization and network-level virtualization, which set the theoretical tone for the research of virtualized WSN. The author of [24] introduced simultaneously wireless information and power transfer (SWIPT) technology to improve the energy efficiency of a WSN with considerations of various physical layer parameters. However, sensor nodes could only send quite limited amount
of data in a single time slot, and the transmission power was low, so the SWIPT technology could not bring much performance gain in practical.

In summary, the mentioned related works [17]–[24] provided various strategies to reduce energy consumption and thus prolong life cycle of sensors under different constraints. However, such strategies are all only based on the ideas of resource optimization or energy harvesting, where the combination of such two ideas is still absent in a WSN scenario. In this paper, we address this open problem and study the resource allocation strategy for a WSN with consideration of WET technology.

III. SYSTEM MODEL
A. NETWORK MODEL
Compared to traditional services, the energy consumption of sensor nodes for multimedia services is relatively higher. If the energy of some sensor nodes is exhausted, the topology of network will change dynamically. In this paper, WSN resources are allocated reasonably with the help of WET to achieve the goal that the physical sensor nodes can serve multiple applications concurrently.

As depicted in Fig. 1, the considered virtualized WSN consists of three layers, i.e., the infrastructure layer, the network service layer and the application layer. In the infrastructure layer, the sensor nodes are managed by the wireless sensor network infrastructure provider (WSN-IP), and WET technology is used in each cluster. The routing topology formed by multiple WSN-IP deployed physical nodes is represented by an undirected graph \( G^S(N^S, L^S) \), where \( N^S = \{N_1^S, N_2^S, \ldots, N_N^S\} \) represents a set of available physical sensor nodes, and \( L^S \) represents a set of links that can communicate with each other within the communication range. Besides, let \( p_i = (f_{i}^{\text{max}}, p_{i}^{\text{max}}, e_{i}^{\text{cur}}) \) denote the vector function of sensor node \( i \), where the three parameters therein denote the maximum data sensing frequency, the maximum data transmission power and the current residual energy of sensor node \( i \) respectively.

The network service layer provides a platform to pool compute, memory, energy, and communication resources of the physical sensor nodes. These resources are virtualized and managed centrally by wireless sensor network service provider (WSN-SP), also including life cycle management, resource pricing, congestion control, etc. At the same time, the central controller is connected to the application layer. According to the request from the wireless sensor network application provider (WSN-AP) in the application layer, the central controller quickly constructs a network slice to provide one-to-one service for a specific application based on a given resource allocation strategy.

In the application layer, the application agent is response for requirement analysis of the applications. On the one hand, WSN-AP transmits demand information to assist WSN-SP in resource allocation. On the other hand, the application agent analyzes the received data, sends it to the corresponding application, and assists the application to make the corresponding decision. Besides, let \( A = (A_1, A_2, \ldots, A_K) \) represents application to be processed in the network. In this paper, the diversity of application types is represented by the amount of data required per unit time, that is, the requirement parameter of the application is specifically expressed as \( O_j = (D_j) \).

When WSN-AP initiates a request to WSN-SP, WSN-SP leases physical sensor node resources from WSN-IP and maps their resources to VSN to provide personalized services for different applications. The specific mapping process is shown in Fig. 2. From the Fig. 2, we can see, when a node in the resource pool is mapped to more than one VSN, there is a contention for the corresponding physical node resource. Therefore, it is necessary to carry out flexible management of sensor node resources, realizing the virtualized WSN and improving resource utilization of the underlying physical infrastructure.

B. COMMUNICATION MODEL
The physical sensor nodes in the infrastructure layer adopt the classical LEACH distributed clustering protocol, and the nodes within the cluster can communicate with the cluster head (CH) by single-hop. CHs are charged by the energy car according to the established route, that is, energy of CHs is sufficient [25]. Under time-division multiplexing mode, the active sensor nodes sense data continuously at a certain frequency. At the beginning of each frame, CH charges the active sensor nodes in the cluster through WET technology for some time slots. Since the power of WET is large enough,
the energy harvested by sensor nodes from noise and other interference signals can be ignored. In the remaining time slots of each frame, the data of each task carried on the sensor node is transmitted to the CH, and finally to the sink node by the CH through multi-hop transmission.

Specifically, as shown in Fig. 3, under time-division multiplexing mode, the frame length is \( T_{\text{max}} \). In phase of energy harvesting, the CH transmits its own energy to the sensor nodes as a radio frequency signal, and then the sensing unit of sensor node \( i \) monitors the sensing object with a constant frequency. Note that the sensing frequency is constant throughout one frame but may changed dynamically across different frames according to application requirements. At the same time, all active sensor nodes in the data sensing phase hold as

\[
\sum_{j=1}^{K} D_{i,j}^f \leq \alpha f_i T_{\text{max}}, \quad \forall i, j
\]

(1)

where \( \alpha \) denotes the data aggregation parameter that is introduced to ensure the energy of collected data [26].

Due to the different performance of sensor nodes, \( C_i^j \) is used to represent the number of CPU revolutions required by sensor node \( i \) to collect data every 1 bit. At the same time, WSN-IP can adjust the sensing frequency \( f_i \) to control the energy consumption of a single node. The energy consumption model for sensor node \( i \) is given as follows

\[
E_i^c = \kappa C_i^j f_i^3 T_{\text{max}},
\]

(2)

where \( \kappa \) is the effective capacitance coefficient of CPU processing unit [27], which is determined by the performance of the hardware. Thus, the energy consumption of all sensor nodes in the data sensing phase holds as

\[
E_c = \sum_{i=1}^{N} E_i^c = \sum_{i=1}^{N} \kappa C_i^j f_i^3 T_{\text{max}}.
\]

(3)

B. ENERGY HARVESTING PHASE

In energy harvesting phase, each CH broadcasts an RF signal to all sensor nodes in the cluster by transmission power \( P_0 \). In addition, the channel power gain between CH and sensor node \( i \) is denoted by \( h_i \). During the first \( \tau_H \) time slots in each frame, all active sensor nodes harvest the energy from the RF signal, and \( \tau_H \) should be satisfied

\[
0 \leq \tau_H \leq T_{\text{max}}.
\]

(4)

The non-linear relationship between energy conversion efficiency and source power can be represented by \( \eta_i(P_0) = 1 - e^{-\phi(P_0 - P_{0_{\text{min}}})} \), where \( \phi \) denotes the fixed parameter of RF antenna and energy management circuit, \( P_{0_{\text{min}}} \) denotes the minimum source power that can activate the energy harvesting unit of sensor node \( i \). In each frame, the energy harvested by sensor node \( i \) is

\[
E_i^H = \eta_i(P_0) \varsigma_i \tau_H P_0 h_i.
\]

(5)

where \( \varsigma_i \) represents the receiving ratio of RF signals. Then, we the total energy harvested by all sensor nodes in each frame can be obtained as

\[
E_H = \sum_{i=1}^{N} E_i^H = \sum_{i=1}^{N} \eta_i(P_0) \varsigma_i \tau_H P_0 h_i.
\]

(6)

IV. GENERAL OPTIMIZATION FRAMEWORK

The virtualized WSN with WET in this paper mainly includes three phases, i.e., data sensing phase, energy harvesting phase and data transmission phase. More specifically, considering the scenario with \( K \) different types of applications competing for \( N \) heterogeneous sensor nodes. The data sensing frequency, time slot configuration for energy harvesting and data transmission, and transmission power of each sensor node are jointly optimized to minimize the network energy consumption.

A. DATA SENSING PHASE

The nodes on VSN\(_j\) need to work together to collect corresponding data for application \( j \). The requirement of data volume for application \( j \) is denoted by \( D_j^f \), the data volume of application \( j \) undertaken by sensor node \( i \) is denoted \( D_{i,j}^f \). Hence, there holds \( \sum_{i=1}^{N} D_{i,j}^f = D_j^f \). In each frame, the total data volume undertaken by sensor node \( i \) holds as \( \sum_{j=1}^{K} D_{i,j}^f \).

In data sensing phase, the sensing frequency of sensor node \( i \) should be satisfied as

\[
\sum_{j=1}^{K} D_{i,j}^f \leq \alpha f_i T_{\text{max}}, \quad \forall i, j
\]

(1)

where \( \alpha \) denotes the data aggregation parameter that is introduced to ensure the energy of collected data [26].

Due to the different performance of sensor nodes, \( C_i^j \) is used to represent the number of CPU revolutions required by sensor node \( i \) to collect data every 1 bit. At the same time, WSN-IP can adjust the sensing frequency \( f_i \) to control the energy consumption of a single node. The energy consumption model for sensor node \( i \) is given as follows

\[
E_i^c = \kappa C_i^j f_i^3 T_{\text{max}},
\]

(2)

where \( \kappa \) is the effective capacitance coefficient of CPU processing unit [27], which is determined by the performance of the hardware. Thus, the energy consumption of all sensor nodes in the data sensing phase holds as

\[
E_c = \sum_{i=1}^{N} E_i^c = \sum_{i=1}^{N} \kappa C_i^j f_i^3 T_{\text{max}}.
\]

(3)

B. ENERGY HARVESTING PHASE

In energy harvesting phase, each CH broadcasts an RF signal to all sensor nodes in the cluster by transmission power \( P_0 \). In addition, the channel power gain between CH and sensor node \( i \) is denoted by \( h_i \). During the first \( \tau_H \) time slots in each frame, all active sensor nodes harvest the energy from the RF signal, and \( \tau_H \) should be satisfied

\[
0 \leq \tau_H \leq T_{\text{max}}.
\]

(4)

The non-linear relationship between energy conversion efficiency and source power can be represented by \( \eta_i(P_0) = 1 - e^{-\phi(P_0 - P_{0_{\text{min}}})} \), where \( \phi \) denotes the fixed parameter of RF antenna and energy management circuit, \( P_{0_{\text{min}}} \) denotes the minimum source power that can activate the energy harvesting unit of sensor node \( i \). In each frame, the energy harvested by sensor node \( i \) is

\[
E_i^H = \eta_i(P_0) \varsigma_i \tau_H P_0 h_i.
\]

(5)

where \( \varsigma_i \) represents the receiving ratio of RF signals. Then, we the total energy harvested by all sensor nodes in each frame can be obtained as

\[
E_H = \sum_{i=1}^{N} E_i^H = \sum_{i=1}^{N} \eta_i(P_0) \varsigma_i \tau_H P_0 h_i.
\]

(6)
C. DATA TRANSMISSION PHASE
In data transmission phase, the channel power gain from sensor node $i$ to CH is denoted by $g_i$. In each frame, sensor node $i$ is allocated $\tau_{i,j}$ time slots to transmit data to application $j$ with power $p_{i,j}$. The time slot configuration is constrained by

$$\sum_{j=1}^{K} \tau_{i,j} + \tau_H \leq T_{\text{max}}, \quad \forall i, j, \quad (7)$$

$$0 \leq \tau_{i,j} \leq T_{\text{max}}, \quad \forall i, j.$$  

The reachable rate of sensor node $i$ for application $j$ holds as

$$r_{i,j} = B_i \log_2(1 + \frac{p_{i,j}g_i}{N_0B_i}), \quad (8)$$

where $B_i$ denotes the link bandwidth between sensor node $i$ and CH, and $N_0$ denotes the spectral density of additive white gaussian noise. Thus, in each frame, the total amount of data transmitted by sensor node $i$ holds as

$$D'_{i} = \sum_{j=1}^{K} \tau_{i,j}B_i \log_2(1 + \frac{p_{i,j}g_i}{N_0B_i}), \quad (9)$$

The amount of data collected by application $j$ holds as

$$D^b_j = \sum_{i=1}^{N} \tau_{i,j}B_i \log_2(1 + \frac{p_{i,j}g_i}{N_0B_i}). \quad (10)$$

Furthermore, the data volume transmitted by a sensor node should not be less than the data volume undertaken by such node itself, and the data volume sent by the sensor node must not be greater than to the data volume collected by the sensor node in the frame. Hence, we have

$$\sum_{j=1}^{K} D'_{i,j} \leq D'_i \leq \alpha_i T_{\text{max}}, \quad \forall i, j, \quad (11)$$

$$D'_j \leq D^b_j, \quad \forall i, j. \quad (12)$$

In addition, the data transmission power should be constrained by

$$0 \leq p_{i,j} \leq p_{i,j}^{\text{max}}, \quad (13)$$

where $p_{i,j}^{\text{max}}$ is the maximum transmission power under the hardware constraint of the data transmission unit.

In general, during the WIT phase, the energy consumption for data transmission at sensor node $i$ holds as

$$E'_i = \sum_{j=1}^{K} p_{i,j} \tau_{i,j}. \quad (14)$$

The total amount of transmitted data of the system can be obtained as

$$D_t = \sum_{j=1}^{K} \sum_{i=1}^{N} \tau_{i,j}B_i \log_2(1 + \frac{p_{i,j}g_i}{N_0B_i}). \quad (15)$$

Finally, the total energy consumption of the system for data transmission holds as

$$E_t = \sum_{j=1}^{K} \sum_{i=1}^{N} p_{i,j} \tau_{i,j}. \quad (16)$$

D. NETWORK ENERGY CONSUMPTION MINIMIZATION
In this subsection, we consider the scenario where multiple applications with different requirements share the same set of infrastructures. The objective is to design an efficient resource allocation strategy to reduce the network energy consumption on the premise of meeting the personalized needs of each application. We focus on the pooled node energy and communication resources in the network service layer, while aiming at optimizing the sensing frequency, time slot configuration and transmission power of the physical nodes in contention. In this paper, the network energy consumption is defined as:

$$E_{\text{all}} = E_c + E_t - E_H. \quad (17)$$

It includes energy consumption of data collection $E_c$, energy consumption of data transmission $E_t$ and energy consumption gain $-E_H$ brought by energy harvesting. Since the energy required to pool physical resources is independent of the optimized factors, the virtualization overhead is ignored in this paper to reduce the analysis complexity. The network energy consumption minimization problem is denoted as P1, which can be expressed as

$$\min_{f_i^*, \tau_{i,j}} E_{\text{all}} = \sum_{i=1}^{N} \kappa C_i f_i^* T_{\text{max}} + \sum_{j=1}^{K} \sum_{i=1}^{N} p_{i,j} \tau_{i,j}$$

$$- \sum_{i=1}^{N} \eta_i \xi_i \tau H P_0 h_i$$

s.t. $\sum_{i=1}^{N} C_i = (1)(4)(7)(11)(12)(13)$

$$C7 : E_i' + E_j' \leq E_i^H + e_i'^{\text{cur}} \quad (18)$$

In P1, constraints C1-C6 have been explained before. In C7, $e_i'^{\text{cur}}$ denotes the current remaining energy of sensor node $i$. This constraint is to ensure the energy operability of sensor node $i$ in the frame, i.e., to ensure that the node continuously monitors the sensing object and sends the collected data to CH with sufficient energy.

V. DYNAMIC RESOURCE ALLOCATION STRATEGY
For the network energy consumption minimization problem where a sensor node is used by multiple applications at the same time, the analysis of objective function in (18) shows that energy consumption increases monotonically with sensing frequency. Therefore, in the premise of meeting the requirements of different applications, reducing the data sensing frequency as much as possible can effectively reduce its own energy consumption and do not bring the negative effects to the energy harvesting and data transmission phases. Hence, the optimal frequency $f_i^*$ can be obtained according to (1), there holds

$$f_i^* = \min(f_i^{\text{max}}, \frac{K}{\sum_{j=1}^{K} D'_{i,j}/\alpha/T_{\text{max}}}). \quad (19)$$

In terms of the practical working mechanism of the sensor nodes, if the time spent in collecting the data required by the application fills the whole frame, it’s certain that the sum of energy harvesting time and data transmission time is
equal to \( T_{\text{max}} \). Otherwise, the data will be randomly filled and sent to the corresponding application, which will completely exceed the controllable range of data aggregation. To this end, we conclude that the sum of time spent for the downlink WET and the uplink WIT is equal to the frame length.

**Theorem 1:** In a virtualized WSN system with WET, the minimum energy consumption of system can only be achieved when the energy harvesting and data transmission use up all the frame \( T_{\text{max}} \), i.e.,

\[
\sum_{j=1}^{K} \tau_{ij}^* + \tau_H = T_{\text{max}}. \tag{20}
\]

**Proof:** We can prove through contradiction. Suppose that when \( \sum_{j=1}^{K} \tau_{ij}^* + \tau_H < T_{\text{max}} \), \( \{ (f_i^*), \{ \tau_{ij}^* \}, \tau_H, \{ p_{ij}^* \} \} \) is a reasonable solution which satisfied (7) to meet minimum energy consumption of system whose target data volume is \( \sum_{j=1}^{K} D_{ij}^* \). Now, the energy consumed by whole system is

\[
E_{\text{all}}^* = E_i^* + E_t^* - E_H^* = \sum_{i=1}^{N} \kappa C_i f_i^* T_{\text{max}} + \sum_{j=1}^{K} \sum_{i=1}^{N} p_{ij}^* \tau_{ij}^* - \sum_{i=1}^{N} \eta_i \xi_i \tau_H P_0 h_i. \tag{21}
\]

Then, we construct another solution \( \{ \tilde{f}_i \}, \{ \tilde{\tau}_{ij} \}, \tilde{\tau}_H, \{ \tilde{p}_{ij} \} \) with \( \{ \tilde{f}_i \} = \{ f_i^* \}, \{ \tilde{\tau}_{ij} \} = \{ \tau_{ij}^* \}, \tilde{\tau}_H = T_{\text{max}} - \sum_{j=1}^{K} \tau_{ij}^* \), \( \{ \tilde{p}_{ij} \} = \{ p_{ij}^* \} \). Firstly, it’s obvious that it can meet system requirements for data volume. Then, it’s easy to check that \( \{ \tilde{f}_i \}, \{ \tilde{\tau}_{ij} \}, \tilde{\tau}_H, \{ \tilde{p}_{ij} \} \) still satisfies constrain C2-C3. Under this allocation, the system’s energy consumption is

\[
\tilde{E}_{\text{all}} = \tilde{E}_i + \tilde{E}_t - \tilde{E}_H = \sum_{i=1}^{N} \kappa C_i \tilde{f}_i^3 T_{\text{max}} + \sum_{j=1}^{K} \sum_{i=1}^{N} \tilde{p}_{ij} \tilde{\tau}_{ij} - \sum_{i=1}^{N} \eta_i \xi_i \tilde{\tau}_H P_0 h_i.
\]

By comparing (21) and (22), it can be seen that the energy consumptions caused by data sensing and data transmission are the same. But \( \tau_{ij}^* < T_{\text{max}} - \sum_{j=1}^{K} \tau_{ij}^* = \tilde{\tau}_H \), so \( E_{\text{all}}^* > \tilde{E}_{\text{all}} \), i.e., \( \{ (f_i^*), \{ \tau_{ij}^* \}, \tau_H, \{ p_{ij}^* \} \} \) is not the optimal solution. Theorem 1 is thus proved.

To sum up, sensor nodes in the data sensing phase should complete the required amount of data exactly within the frame, under the premise of data aggregation. The time slot configuration for energy harvesting and data transmission should use up all each frame. We propose a resource allocation scheme for jointly optimizing the sensing frequency, time slot configuration and power transmission to minimize energy consumption for a powered virtualized WSN denoted by PVWec. The proposed scheme is summarized in Algorithm 1.

### Algorithm 1 Solving P1 for Minimum PVWec

1. **Input:** \( N, K, A, P_0 \)
2. **output:** \( \{ (f_i^*), \{ \tau_{ij}^* \}, \tau_H, \{ p_{ij}^* \} \} \)
3. **Initialize:** \( B, g, h, \alpha, \epsilon, \theta \)
4. for each \( i \in N \) do
   5. Compute \( \sum_{j=1}^{K} D_{ij}^* \) by sum(A).
6. \( f_i^* = \min_{f_i^*} = \sum_{i=1}^{K} D_{ij}^*/\alpha/T_{\text{max}} \).
7. **end for**
8. Replace C2-C3 with (20) to update P1.
9. while optimalitytolerance \( > \theta \) do C7 is not satisfied do
10. Set starting value \( \{ (\tau_{ij}), \tau_H, \{ p_{ij} \} \} \) which is satisfied with P1.
11. Get a matrix of linear constraints \( \rightarrow (20) \).
12. Get a constraint on the upper and lower bounds of the transmission power \( \rightarrow C6 \).
13. Get a matrix of nonlinear constraints \( \rightarrow C4-C5 \).
14. Using ‘fmincon’ to find minimum of (17).
15. **end while**
16. **END**

### TABLE 1. Simulation parameters.

| Symbol                        | Quantity          |
|-------------------------------|-------------------|
| The ratio of data aggregation \( \alpha \) | 50\%              |
| CPU revolutions for per unit of data \( C_i^* \) | 1000              |
| Coefficient of capacity \( k \) | 10~18             |
| Noise spectral density \( N_0 \) | -174dBm/Hz       |
| Channel gain of WET \( h_i \) | 1.5               |
| The receiving ratio of RF signals \( \zeta \) | 20\%              |
| Applications’ required data volume \( D_{ij}^* \) | 100-2000bits     |
| Link bandwidth \( B \)         | 200-400kb/s       |
| Sensor node power in saturation | 5J               |
| The power of CH in WET         | 0.3-5W            |

### VI. SIMULATION RESULTS

In this section, we evaluate the performance of the resource allocation scheme named PVWec with the help of MATLAB. Various power configurations of WET and application types are considered in the simulation. Note that the application type is characterized by the amount of data required per unit time. More specifically, we deploy 100 sensor nodes which belong to two different WSN-IP in the 100m*100m scenario, and the communication range of each sensor node is 10m-20m. In addition, the remaining parameters determined by the network itself are listed in Table 1. For all the cases, results are obtained through averaging the outcome of 100 realizations.

Fig. 4 shows the physical distribution of sensor nodes. It can be seen that there are one hundred sensor node from two WSN-IPs, deployed in a range of 100m*100m to sense data in their respective monitoring areas. With the cooperation of clustering protocol, CHs can perform WET for sensor nodes in its own region, and the sensor nodes can send the perceived data to the corresponding CH.
Fig. 5 compares the relationship between energy consumption and CH energy charging power in a single time slot for several types of applications in the PVWec scheme. In this simulation, three task types are considered, which refer to big data request, medium data request and small data request, and the required data volume in per unit time is 1000 bits, 500 bits and 100 bits, stand for video streams, photo pixels, and numerical floats respectively. In addition, the tasks compete for ten sensor nodes from two different WSN-IPs (i.e., two types of nodes). In Fig. 5, big data volume refers to that both types of nodes are big data requested, medium data volume refers to that both types of nodes are medium data requested, similarly, small data volume refers to that both types of nodes are small data requested. It is worth mentioning that mixture data volume refers to the two types of nodes are big data requested and medium data requested, respectively. As we can see from the figure, in the beginning, the energy consumption of sensor nodes is fixed at a positive value. When the energy transmission power increases to a certain degree, the energy consumption of sensor nodes starts to decrease and even falls below 0. This is because when $P_0$ is too small, the minimum source power of RF signal that can be harvested by the sensor node is not reached. In this case, the sensor node can only consume its own inherent energy. When $P_0 > P_{min}$, the sensor can harvest energy to compensate for its own energy consumption. Even more, when is $P_0$ large enough, the sensor node can harvest more energy and store it in its own battery. Such behavior can be used to support sensor nodes to sense objects and transmit data after the energy car travels away. In addition, it is observed that larger data demand consumes more energy. Under the same power of WET, the ratio of energy supplement is inversely proportional to the total task amount of all the nodes. This is because when the time slot is allocated, the larger data requested, the less time for WET allocated. In general, in practical applications, the power of WET can be managed according to the amount of data required by the applications, so as to achieve the goal of not wasting the energy of CH and supplementing enough energy for sensor nodes at the same time.

In Fig. 6, the residual energy of sensor nodes which contented by different types of applications is compared. The simulation scenario is the same as Fig. 5. Besides, the wireless charging power of CH is set to 0.15W. As shown in Fig. 5, for big data application and mixture data application, the energy harvested by sensor nodes can only alleviate the energy consumption caused by information sensing and transmission when $P_0 = 0.15W$, i.e., no energy can be stored. Conversely, for medium data application and small data application, the sensor node can reach the state of power storage. Such observations are also confirmed in Fig. 6. In detail, for big data and mixture data applications, the residual energy of sensor nodes gradually decreases until the energy is used up. For medium data and small data applications, the energy of sensor nodes gradually increase until saturation. It’s worth mentioning that when the battery of a sensor node is saturated, such sensor does not harvest energy in the next time slot, which avoids energy leakage and waste.
In Fig. 7, the relationship between the data demanded and the residual energy is depicted. The remaining energy of a single sensor node is set to 2.5J in the initial state and the total saturated energy of the ten contended nodes is set to 50J. In the simulation, the number of tasks is increased at the frequency of 100bits/10000s. The evolution of sensor nodes’ residual energy is continuously observed within $1.2 \times 10^5$ s. As observed, with the continuous increase of data demand, the residual energy of sensor nodes increases first and then decreases. This is because when the data demand is small, the energy harvested by the sensor nodes is greater than the energy consumed. Hence, the WET mechanism can bring a large gain. As the data demand continues to increase, the energy harvested by the nodes is not enough to make up for the energy consumed, i.e., they need to consume their inherent energy. At the same time, it can also be seen from Fig. 7 that the number of tasks corresponding to the peak value of residual energy of sensor nodes is positively correlated with charging power.

Fig. 8 compares four time slot allocation schemes when multiple sensor nodes are competed by multiple applications, including the PVWec scheme proposed in this paper, the TS-rat allocation scheme which allocates $\tau_{i,j}$ for application under the ratio of $D'_{i,j}/\sum_{j=1}^{K} D'_{i,j}$, the TS-equ allocation scheme with identical time slot allocation for each application, and the TS-rand allocation scheme with random time slot allocation to each application. Also, we set $P_0 = 0.15W$. It is observed that no matter how much the data demand increases, the proposed PVWec scheme always guarantees lowest energy consumption compared to the other schemes. However, the advantage of PVWec scheme decreases with the increase of data request volume. The reason is that the CHs’ power of WET is not large enough and the maximum energy gain is $\sum_{i=1}^{N} \eta_i \zeta_i P_0 h_i T_{\text{max}}$. In order to minimize energy consumption, the system needs to allocate more time for WIT phase when data demand is high.

Fig. 9 shows the gain brought by the WET technology to virtualized WSN. In the simulation, we set $P_0 = 0.12W$. However, compared with the virtualized WSN without WET technology, the difference in energy consumption between the two schemes increases when the data demanded by applications decreases. This is in line with the previous conclusion, i.e., when the volume of data demand is large, the gain brought by the low power of WET is so small that the system will not allocate large time slots for energy harvesting. From this, if the power of WET is fixed and the data demand volume is infinite, the energy consumption of the wireless powered virtualized sensor network is approximately equal to the virtualized network without WET technology.

Fig. 10 compares the data throughput performance of each application. We consider two cases where the first case includes two types of applications and the second cases includes three types of applications. Note that the resources under such two cases are different. It can be seen from the simulation results that when two applications access
the network, the data throughput of these two applications are similar. When the system accepts the third application, the data throughput redistributed, and then the throughput of each application is also almost the same. Due to the increase in volume of data required by application, the overall data throughput increases. This shows that the proposed scheme can not only realize the sensor nodes to serve multiple applications simultaneously and improve the WSN physical resource utilization, but also achieve fair resource competition among different applications.

VII. CONCLUSION

In this paper, we studied the resource allocation problem of wireless powered sensor network where sensor nodes served multiple applications simultaneously. By pooling the sensor nodes’ communication, calculation, energy and other resources together, a one-to-one service mode between VSN and application was formed. Also, we proposed a resource allocation scheme to jointly adjust sensing frequency, time slot configuration and data transmission power to minimize the network energy consumption caused by serving different types of applications. Simulation results verified that the proposed scheme enabled resource sharing among different sensor nodes, effectively minimized network energy consumption and guaranteed fair competitions among different applications. The analysis in this paper sheds new light in resource multiplex among different applications for wireless sensor networks.

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