energies

MDPI

Article

Optimal Sensor Association and Data Collection in Power Materials Warehouse Based on Internet of Things

Fangqiuzi He [1], Junfeng Xu [2], Jinglin Zhong [3], Guang Chen [4] and Shixin Peng [5,*]

1 School of Art and Design, Wuhan Polytechnic University, Wuhan 430074, China; fangqiuzihe@163.com
2 Wuhan Maritime Communication Research Institute, Wuhan 430074, China; amongxu@163.com
3 Department of Mathematics, University of Calgary, Calgary, AB T2N 1V4, Canada; Jinglin.zhong1@ucalgary.ca
4 School of Mechanical Engineering and Electronic Information, China University of Geosciences (Wuhan), Wuhan 430074, China; cguang12019@cug.edu.cn
5 National Engineering Laboratory for Educational Big Data, Central China Normal University, Wuhan 430079, China
* Correspondence: pengshixin@mail.ccnu.edu.cn; Tel.: +86-150-0278-7428

Abstract: In order to realize the intelligent management of a power materials warehouse, the Internet of Things based on wireless sensor networks (WSNs) is a promising effective solution. Considering the limited battery capacity of sensor nodes, the optimization of the topology control and the determination of the amount of collected data are critical for prolonging the survival time of WSNs and increasing the satisfaction of the warehouse supplier. Therefore, in this paper, an optimization problem on sensor association and acquisition data satisfaction is proposed, and the subproblem of the sensor association is modeled as the knapsack problem. To cope with it, the block coordinate descent method is used to obtain the suboptimal solution. A sensor association scheme based on the ant colony algorithm (ACO) is proposed, and the upper and lower bounds of this optimization problem are also obtained. After this, a cluster head selection algorithm is given to find the optimal cluster head. Finally, the experimental simulations show that the algorithms proposed in this paper can effectively improve the energy utilization of WSNs to ensure the intelligent management of a power materials warehouse.

Keywords: power materials warehouse; wireless sensor network; topology control; Internet of Things; data collection

check for updates

Citation: He, F.; Xu, J.; Zhong, J.; Chen, G.; Peng, S. Optimal Sensor Association and Data Collection in Power Materials Warehouse Based on Internet of Things. *Energies* **2021**, *14*, 7449. https://doi.org/10.3390/en14217449

Academic Editor: Sergio Saponara

Received: 14 October 2021
Accepted: 5 November 2021
Published: 8 November 2021

1. Introduction

With the rapid development of the logistics industry and smart grid, the intelligent management of a power materials warehouse has become more and more important [1]. Power materials warehouse management is a key component of ensuring a smooth material distribution and the overall efficiency of the smart grid, and is also recognized as one of the most effective ways of reducing labor requirements. Smart warehouse systems rely on the development of modern warehouse system technology, optimized structural design, computer technology, distributed control technology and communication technology that can be adjusted in function of the internal and external environments [2,3]. Compared with traditional warehouse systems, intelligent warehouse systems are more energy efficient, easier to maintain, and have become the future development trend of warehousing. An efficient and intelligent platform is provided for the warehouse manager while ensuring the economic operation and intelligent management of the warehouse system which is the core pillar of the intelligent storage system [4]. As a subsystem of the intelligent warehouse system, the wireless sensor network (WSN) monitors the temperature and humidity of the internal and external environment of the storage system, reasonably dispatches the intelligent storage system according to appropriate strategies and minimizes the energy consumption of the intelligent storage system while ensuring commercial circulation. Therefore, the industrial wireless sensor networks (iWSNs) system occupies a very important position of the intelligent management of a power materials warehouse.

WSNs are an emerging technology that promises to provide real-time information collection, sensing, processing and transmission in a variety of different scenarios [5]. Deploying WSNs to a power materials warehouse based on the Internet of Things plus makes the warehouse intelligent and endlessly monitored by sensors collecting physical or environmental parameters such as temperature, sound, vibration and pressure. The information collected by sensors plays a key role in warehouse management and protection [6]. Wireless sensor networks have the advantages of being low cost with dynamic networking and being deployable and scalable, which can complete the collection and transmission of the state data of each object in the smart warehouse and realize the relevant functions of the smart warehouse system so that the smart warehouse system can operate safely and stably. The impact of data collection on the accuracy of sensing plays a key role in the management and protection of power materials. Therefore, the utility of data acquisition is considered in this paper. In the power materials warehouse, the WSNs consist of a large number of densely deployed sensor nodes with limited resources and limited processing and battery capacity [7]. The limited energy is a key concern in reducing the distortion of transmitted data and prolong the lifetime of the sensor network. Meanwhile, the wireless resource allocation and quality of service (QoS) requirements of cluster members (CMs) that may result in inefficient and unreliable communication between nodes means that sensor nodes will need to consume more energy. Nodes at the edge of the cluster may be assigned to clusters with low transmission rates, resulting in large latency and high power consumption for information transmission. How to effectively cluster sensor nodes to achieve a balance of energy consumption and data collection satisfaction of sensor nodes is a key research direction [8].

Based on the above research, this paper investigates the joint optimization of sensor association, data collection satisfaction and cluster head selection for the intelligent management of a power materials warehouse, while considering the constraints of the sensors' capacities. The energy consumption of sensor nodes mainly consists of data acquisition energy consumption and transmission energy consumption. Generally speaking, the larger the amount of data collected, the higher the monitoring accuracy and data satisfaction. However, this also leads to data redundancy and excessive energy consumption, so a weight balance between the energy consumption of sensors and data satisfaction needs to be achieved. The main contributions of this paper are as follows:

1. This paper integrates the data collection satisfaction and sensor association for wireless sensing networks in a power materials warehouse of smart grid and constructs a joint optimization problem. Finally, a high-quality suboptimal solution was found by the BCD algorithm;
2. On the basis of finding the optimal amount of collection data, sensor association is reduced to a knapsack problem, and the ACO-based sensor association scheme is proposed to solve the problem. The practical simulations show that the gap of the suboptimal solution obtained by this algorithm is relatively small.
3. The optimal sensor association and cluster head selection are also obtained to achieve an optimal topology control strategy for the WSNs.

2. Literature Review

For sensor networks, how to improve energy efficiency and prolong the network life are important issues worth considering. General research is divided into three categories, including clustering, cluster head selection and clustering protocol [9].

Clustering is one of the ways to solve the energy consumption of data transmission. A new distributed clustering method was proposed for long-lived wireless sensor networks which is effective in prolonging the network life and supporting scalable data aggregation [10]. For periodically collecting data, a new clustering mode called EECS was proposed for wireless sensor networks, which selects cluster heads (CHs) with more residual energy and balances the load among CHs, thus effectively prolonging the service life of sensor networks [11]. For the data packet loss in mobile sensor networks, an improved low-energy adaptive clustering hierarchical protocol was proposed. The fuzzy inference system can not only prolong the network life, but also reduce the packet loss [12].

The optimal CH selection can reduce the total energy consumption and balance the load. According to the residual energy parameters of CHs and the number of members in the previous process, a reward-based clustering algorithm was proposed to periodically select CHs by learning methods [13]. Under the consideration of energy saving, a CH selection algorithm was proposed to select CHs by the density of member nodes and the distance from CHs, which is more energy efficient than only considering the distance between nodes [14]. Secondly, based on the CH selection process, a distributed channel selection algorithm was proposed, which balances the energy consumption between sensors based on the distance between sensors and base stations [15]. With the objective of optimal head selection in hierarchical topology control, a solution based on fuzzy clustering and particle swarm optimization was proposed, mainly aimed at CH selection in hierarchical topology control, reducing the node mortality rate and prolonging the network life cycle [16]. Then, a CH selection based on energy-efficient mobility was proposed to achieve the channel selection and load balancing based on special parameters, which have a great impact on sensor energy consumption [17].

The development of wireless sensor networks has led to the emergence of many communication routing protocols. A low-energy adaptive clustering hierarchy (LEACH) was developed and analyzed, which is a protocol architecture for micro-sensor networks. It combines the ideas of cluster-based routing and media access with high energy efficiency and application-specific data aggregation, achieving good performance in terms of system lifetime, delay and application-aware quality [18]. On the basis of LEACH, a new self-organizing energy-saving hybrid protocol based on cluster architecture and multi-hop routing was proposed. The new protocol has better performance in terms of energy efficiency and WSN lifetime [19]. Then, in order to meet the energy and delay constraints of sensor networks, two schemes combining the clustering strategy and chain routing algorithm are proposed. One is a link-based stable election protocol, and the other is a chain routing protocol based on the coordinate-oriented clustering strategy. These two routing protocols optimized the performance of the energy and delay [20]. At the same time, an energy classification protocol architecture based on clustering was proposed to achieve low energy consumption and low delay without sacrificing application-specific quality [21]. In the case that most clustering protocols cannot adjust the corresponding protocol parameters for different sensor networks, a clustering protocol based on a meta-heuristic method (CPMA) was proposed, which can prolong the lifetime of sensor networks better than other protocols [22]. A flexible distributed multi-agent control scheme was proposed, which was composed of three distributed consensus protocols and can achieve optimal power sharing even in communication interference [23].

This paper considers the influence of data collection in the energy efficiency and data accuracy satisfaction of the WSNs, which has rarely been considered in the previous works. Based on optimal data collection, the association of sensors was modeled as a knapsack problem. After that, a framework of the optimization problem consisting of data collection, cluster head selection and sensor association was constructed. The joint optimization of data collection and energy consumption was proposed to obtain the sensor association to maximize the network resource utilization. Meanwhile, a low-complexity cluster head selection method was also used to reduce the compute complexity of the proposed framework.

3. System Model

As shown in Figure 1, we considered a WSN for a smart power materials warehouse, which included goods, transportation equipment and communication equipment. In order to achieve the intelligent management of the entire platform and ensure the safe operation of the entire system, a large number of sensor nodes were deployed, including temperature, humidity, displacement and smoke. The WSNs consisted of N sensors, and the set of sensors is denoted as $\mathcal{N}$ and satisfies $|\mathcal{N}| = N$. Considering the mobility of transport equipment, all sensor node were randomly deployed according to the Poisson point process (PPP) with the deployment density ρ. In order to reduce the WSNs' energy consumption and prolong the survival time, all sensors need to be topologically controlled to transmit data. Assuming that all sensors are divided into K clusters, there are K CHs, and the set of CHs is noted as $\mathcal{K}$. Then, the other $N - K$ sensor nodes are CMs. The sensor nodes are responsible for collecting data and finally transmitting the collected information to the base station for analysis and processing. In the system, the sensor nodes transmit the monitored information to the aggregation point by wireless communication. All sensor nodes are isomorphic and have the same initial energy, data processing capability and communication energy consumption. The location of sensor nodes did not change again after the deployment was completed. The sensor nodes did not move during the whole life cycle, and only died due to energy depletion; there were no additional factors such as equipment damage.

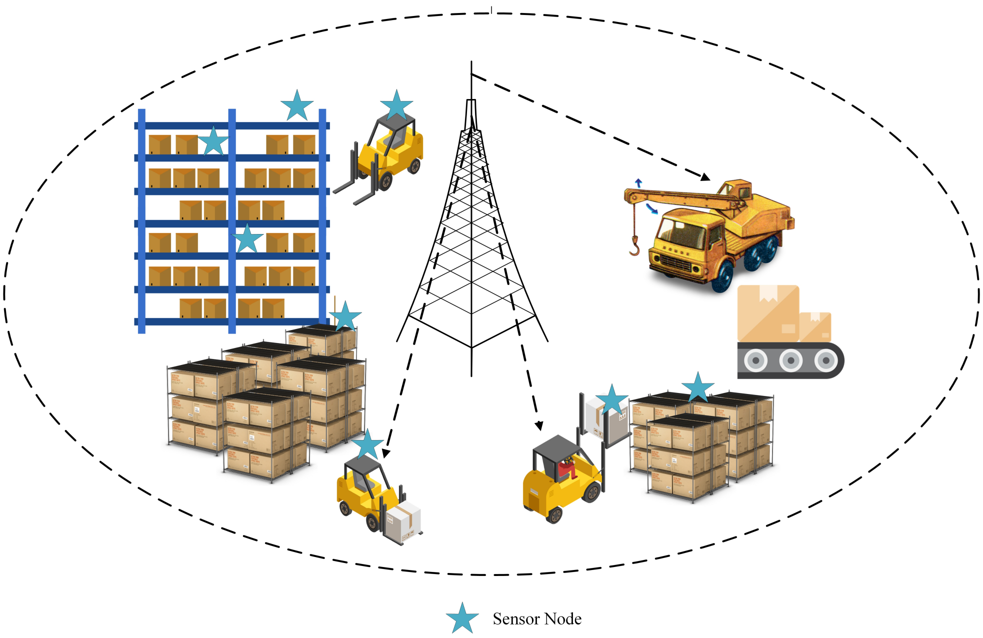

Figure 1. An intelligent power materials warehouse of a smart grid based on WSNs.

The notions are summarized in Table 1.

Table 1. The key notations.

Variable	Parameter
ω_c	Energy consumed per unit of data acquisition
a	Risk aversion coefficient of utility function
M_n	The amount of data collected
η	The efficiency of the power amplifier
P_t	Transmission power
α	Circuit power consumption of data transmission
r	Data transmission rate
e_c	Circuit power for receiving the data
x_{ij}	Association decision
N_{jmax}	Maximum number of CMs that the CH can access
E_{DA}	The energy consumption per bit of data fusion

Energy Consumption Model

The sensor working process needs to collect the data and then upload the collected information. In order to reduce energy consumption in the WSNs, topology control is widely used. The sensor first transmits the collected information to the CH which then fuses the data and transmits them to the base station. For data collection, considering the fact that the energy consumption is related to the amount of data collected, we defined the following energy consumption model for collection:

$$E_{n,c} = w_c \cdot M_n, \tag{1}$$

where w_c is the energy consumed per unit of data acquisition by the sensor, M_n is the amount of data collected by the sensor per round. Sensor data collection will produce a certain amount of error, affecting the quality of the entire power smart warehouse detection of sensors. We can reduce the impact of the error by increasing the amount of data collection.

Therefore, the amount of data collection directly affects the collection satisfaction, and the following utility function is defined to measure our satisfaction with data collection:

$$U(M_n) \;=\; a\left(M_n - \frac{1}{2}aM_n^2\right);\; aM_n \le 1 \tag{2}$$

where $U()$ is the quadratic utility function, which is used in [24,25]. a is the risk aversion coefficient. From this equation, we obtained that the higher the data collection, the higher the satisfaction, however, correspondingly, the higher the energy consumption.

For data transmission, a lot of previous works have used the energy consumption model in [26]. This energy consumption model only considers the data transmission and transmission distance, but does not consider the effect of the wireless channel condition on energy consumption. Therefore, the energy consumption model in [27] is used in this paper. This model considers the data transmission rate, i.e., the channel bandwidth, SNR, etc. The energy consumed by the sensor to transmit M_n bits of data is:

$$E_{n,t} = \frac{1}{\eta}(P_t + \alpha) \cdot \frac{M_n}{r_{n,x}}, \tag{3}$$

where η is defined as the efficiency of the power amplifier; P_t is the transmission power; α is the circuit power consumption of the data transmission; $r_{n,x}$ is the data transmission rate of the sensor node. The energy consumption of the sensor node receiving the M bits data is:

$$E_{n,r} = e_c \cdot M_n, \tag{4}$$

where e_c is the circuit power for receiving the data.

The association decision variable for the sensor i is $x_{ij} \in \{0,1\}$, which indicates whether the sensor i selects the associated CH j. $x_{ij} = 1$ means that the CM i chooses to access the CH j, or else $x_{ij} = 0$. The sensor association decision variables are constrained by

$$\sum_j x_{ij} = 1,\;\; \forall i \in \mathcal{N} \tag{5}$$

$$\sum_i x_{ij} = N_{j\,\max},\;\; \forall j \in \mathcal{K} \tag{6}$$

$$x_{ij} \in \{0,1\},\;\; \forall i \in \mathcal{N}, \forall j \in \mathcal{K} \tag{7}$$

where $N_j^{\max}$ is the maximum number of CMs that the CH j can access. The first constraint indicates that each sensor can only choose to have access to the same CH, and the second constraint imposes limits on the maximum number of associated CMs per CH. Following the energy model adopted in this paper, we can obtain the transmission energy consumption per round of the WSNs. For CMs, the energy consumption can be expressed as

$$E_{CMi} = \frac{1}{\eta}(P_t + \alpha) \cdot M_i \sum_j \frac{x_{ij}}{r_{ij}}, \tag{8}$$

where e_c is the circuit power for data reception. In addition, the CH receives data from all CMs. In order to reduce energy consumption, the received data need to be fused into M_n and then be transmitted to the base station. The energy consumption per bit of data fusion is denoted by E_{DA}.

For the CHs, in addition to consuming energy to collect data, they also consume energy to receive data from CMs before fusing the data and transmitting the fused data to the base station. Thus, the energy expenditure per round of the CHs can be expressed as

$$E_{CHj} = e_c \cdot \sum_i (M_i \cdot x_{ij}) + E_{DA} \cdot \left(\sum_i (M_i \cdot x_{ij}) + M_j \right) + \frac{1}{\eta}(P_t + \alpha) \frac{M_j}{r_{con}}, \tag{9}$$

where r_b represents the transmission rate of the CHs to the base station.

4. Topology Control and Data Collection Satisfaction

The topological control of WSNs mainly includes two aspects: sensor association and CHs selection. In this section, we first constructed an optimization problem to perform sensor association as well as determine the amount of collected data, and then used the block coordinate descent method to alternately obtain a suboptimal solution to the optimization problem. Finally, an optimal CHs selection algorithm was proposed based on sensor association results.

4.1. Problem Formulation

In this part, we constructed the acquisition data determination and sensor association issues designed to maximize satisfaction with the sensor data acquisition and reduce the energy consumption. Note that the amount of data collected for all sensors is $M = \{M_n, n \in \mathcal{N}\}$ and association with the CMs is $X = \{x_{i1}, \cdots, x_{ij}, \cdots, x_{iK}, i \in \mathcal{G}, j \in \mathcal{K}\}$. Joint data collection determination and sensor association optimization problems were constructed as follows:

$$\begin{aligned}
\mathbf{P}\ :\ \max_{M,X}\ & \sum_n a\left(M_n - \frac{1}{2}aM_n^2\right) - \beta\left(\sum_n (w_c M_n) + \sum_{i=1}^{I} E_{CMi} + \sum_{j=1}^{J} E_{CMj}\right) \\
&= \sum_n a\left(M_n - \frac{1}{2}aM_n^2\right) - \beta \sum_n w_c M_n + \sum_{i=1}^{I}\left[\frac{1}{\eta}(P_t + \alpha) \cdot M_i \sum_j \frac{x_{ij}}{r_{ij}}\right] \\
&+ \sum_{j=1}^{J}\left[\sum_i (e_c \cdot M_i \cdot x_{ij}) + E_{DA} \cdot \left(\sum_i (M_n \cdot x_{ij}) + M_j\right)\right]
\end{aligned} \tag{10}$$

$$\begin{aligned}
s.t.\ \ & (5), (6), (7); \\
& 0 < M_n < M_{\max}.
\end{aligned} \tag{11}$$

where $\beta > 0$ is the compromise between satisfaction and energy consumption.

Because the presence of binary variables $x_{ij} \in \{0, 1\}$ causes the problem as the mixed integer programming problem, it is difficult to find the optimal solution. Dynamic programming is widely used to solve the mixed-integer programming problem. However, dynamic programming is inefficient for large-scale problems due to considerable state storage requirements. The rest of this paper is to design a low-complexity algorithm to obtain a suboptimal solution.

4.2. Problem Solution

To address the problem **P**, we sought to iteratively optimize the data collection and sensor association by using a block coordinate descent (BCD) method with convex optimization to obtain a suboptimal solution [28]. In each iteration, we first addressed the amount of collection data problem in a fixed sensor association result **X**. Afterwards, we optimized the sensor association under a given amount of collected data of design **M**. When the proposed algorithm converges to a predetermined accuracy, a suboptimal solution can be obtained.

4.2.1. Data Collection Optimization

Given a sensor association, the optimization problem of the data collection can be recast as

$$\begin{aligned}
\mathbf{P1}:\ \max_{M,X}\ & \sum_n a\left(M_n - \frac{1}{2}aM_n^2\right) - \beta\left(\sum_n (M_n w_c) + \sum_{i=1}^{I} E_{CMi} + \sum_{j=1}^{J} E_{CMj}\right) \\
&= \sum_n a\left(M_n - \frac{1}{2}aM_n^2\right) - \beta\sum_n M_n w_c + \sum_{i=1}^{I}\left[\frac{1}{\eta}(P_t+\alpha)\cdot M_i \sum_j \frac{x_{ij}}{r_{ij}}\right] \\
&+ \sum_{j=1}^{J}\left[\sum_i (e_c \cdot M_i \cdot x_{ij}) + E_{DA}\cdot\left(\sum_i (M_n \cdot x_{ij}) + M_j\right)\right] \\
& s.t.\ \ 0 < M_n < M_{\max}.
\end{aligned} \tag{12}$$

The objective function of this problem is concave and constrained to an affine function, so the problem is a convex optimization problem. We can obtain its optimal solution by using the Lagrangian dual method. The Lagrangian functions and dual problems of this optimization problem are, respectively:

$$\begin{aligned}
L(M,\lambda,\nu) = & \sum_n a\left(M_n - \frac{1}{2}aM_n^2\right) - \beta\left(\sum_n (w_c M_n) + \sum_{i=1}^{I}\left[\frac{1}{\eta}(P_t+\alpha)\cdot M_i \cdot \sum_j \frac{x_{ij}}{r_{ij}}\right]\right. \\
& \left. + \sum_{j=1}^{J}\left[\sum_i (e_c \cdot M_i \cdot x_{ij}) + E_{DA}\cdot\left(\sum_i (M_i x_{ij}) + M_j\right)\right]\ \right) \\
& + \sum_{n=1}^{N} \lambda_n M_n + \sum_{n=1}^{N} v_n (M_{\max} - M_n),
\end{aligned} \tag{13}$$

where $\lambda = \{\lambda_n, \forall n\}, \nu = \{\nu_n, \forall n\}$ is a non-negative Lagrangian multiplier. Then, we can obtain the optimal amount of collection data which is:

$$M_n^* = \begin{cases} \dfrac{a - \left[\beta\left(w_c + \frac{(p_t+\alpha)}{\alpha}\cdot\sum_j \frac{x_{ij}}{r_{ij}} + (e_c + E_{DA})\sum_j x_{ij}\right) - \lambda_n + \nu_n\right]}{a^2} & ,n \text{ is a } CM \\ a - [\beta(w_c+1) - \lambda_n + \nu_n] & ,n \text{ is a } CH \end{cases} \tag{14}$$

After obtaining the optimal, we can solve its corresponding dual problem as follows:

$$\begin{aligned}
& \max_{\lambda,\nu}\ D(\lambda,\nu) \\
& s.t.\ \ \lambda \succ= 0, \\
& \qquad \nu \succ= 0.
\end{aligned} \tag{15}$$

Since the dual problem is concave for Lagrangian multipliers λ and ν, the sub-gradient method can be employed, which guarantees convergence to the global point. Thus, in each iteration, the dual variables are separately given as

$$\lambda_n^{(r+1)} = [\lambda_n^r + s_r t_n]^+, \forall n \in \mathcal{N}; \tag{16}$$

$$\nu_n^{(r+1)} = [\nu_n^r + s_r(T_{\max} - t_n)]^+, \forall n \in \mathcal{N}, \tag{17}$$

where S_r is the step length of the r iteration, whose value is set to $S_r = \beta/||g^r||$; g^r is the current gradient of the dual function of the r-th iteration.

4.2.2. Sensor Association Optimization

When the amount of collection data is given, the sensor association optimization problem is as follows:

$$\begin{aligned} \mathbf{P2}: \ & \min_X (\sum_{i=1}^{I} E_{CMi} + \sum_{j=1}^{J} E_{CMj}) \\ & = \sum_{i=1}^{I} \left[\frac{1}{\eta}(P_t + \alpha) \cdot M_n \sum_j \frac{x_{ij}}{r_{ij}} \right] + \sum_{j=1}^{J} \left[e_c \cdot (M_n \cdot x_{ij}) + E_{DA} \cdot \left(\sum_i (M_n \cdot x_{ij}) \right) \right] \\ & \qquad s.t. \ (5), (6), (7); \end{aligned} \tag{18}$$

The optimization problem is a 0–1 multi-Knapsack problem, and since the 0–1 Knapsack problem is an NP complete problem, this paper presents a sensor association algorithm based on the ant colony algorithm to determine the approximate optimal solution. Furthermore, to evaluate the gap between the suboptimal and the optimal solutions, we relax the problem to a linear programming problem to obtain its upper bound. In addition, we also solve the problem by a greedy algorithm to obtain its lower bound.

4.2.3. ACO-Based Sensor Association Scheme

The rationale of the ant colony algorithm is the optimal discovery path of a group of ants looking for food. In the process of looking for food, each ant will emit pheromones on the path, which will gradually fade as the path grows. Thus, a shorter path will have stronger pheromones, and ants will be more attracted by this path. The stronger the pheromones, the higher the possibility is that ants will choose this path. Meanwhile, when a path is chosen by more ants, the pheromone of this path will also increase, which forms a positive feedback and leads to more ants being attracted to this path and taking it. Finally, ants will find the optimal path [29].

To this end, a colony containing Q ants was constructed, with each ant looking for a suitable path. First, a set of pheromones was initialized; the pheromones were left by ants on the path, attracting the ants to increase the possibility of the path being taken, so when each iteration ends, the pheromones of the path will be updated. Thus, in each iteration, the pheromones of optimal path increase, and the pheromones of the optimal path will decay. Therefore, to model pheromone losses from evaporation, all elements are reduced by multiplying $(1-\rho)$, where $\rho \in [0,1]$. Assuming that the current optimal solution of the problem is denoted as S_{best}, and S represents the best feasible solution obtained during one iteration, if (i,j) belongs to the feasible solution S obtained from this iteration, then the pheromone of (i,j) should be increased by adding γ_i, which reflects the performance of the current solution, which is given as follows:

$$\gamma_i = \frac{f(S)}{f^2(S_{best})}. \tag{19}$$

The pheromone is updated as

$$\tau_{ij}^{(k+1)} = \rho\tau_{ij}^{(k)} + \gamma_i; \tag{20}$$

otherwise, pheromones should be attenuated and expressed as

$$\tau_{ij}^{(k+1)} = \rho\tau_{ij}^{(k)}. \tag{21}$$

At the same time, in order to balance development and exploration, prevent entering search stagnation, the upper and lower bounds are set for pheromones, which are τ_{min} and τ_{max}, respectively. In each iteration, each ant constructs a sensor association scheme following a probabilistic decision. For CM i, ants find all CH sets with an associated CM number less than $N_j^{\max}$, which is denoted by $\mathcal{C}$. Thereafter, the probability of the CM i selecting the CH j is noted as

$$p_{i,j} = \frac{\tau_{i,j}^{\alpha} \cdot \eta_{i,j}^{\beta}}{\sum_{l \in \mathcal{C}} \tau_{i,l}^{\alpha} \cdot \eta_{i,l}^{\beta}}, \tag{22}$$

where $\tau_{i,j}$ and $\eta_{i,j}$ are, respectively, updated pheromones and heuristic information, and α and β determine the influence of pheromones and heuristic information. Pseudo-random scaling rules are also used in the sensor association problem to balance exploration and exploitation. Assuming the exploitation probability is denoted by q_0, the ant chooses the sensor association scheme with the best potential performance; otherwise, the decision is probabilistic and a feasible scheme is randomly chosen. The proposed ACO-based sensor association scheme algorithm is described in the Algorithm 1.

Algorithm 1 ACO-Based Sensor Association Scheme (ACOSA)

Initialize the maximum number of iterations $MaxIter$ and ants $NumAnt$.
Initialize pheromone and heuristic information.
Require: The number of CMs $NumCM$ and CHs $NumCH$, Maximum association number of CHs N_{jmax}.
for $n = 1$ to $MaxIter$ **do**
  for $k = 1$ to $NumbAnt$ **do**
    for $i = 1$ to $NumCM$ **do**
      for $j = 1$ to $NumCH$ **do**
        if the number of CMs associated with CH j is less than N_{jmax} **then**
          Obtain selecting Probability following
        end if
      end for
      if $q < q0$, where $q \sim U(0,1)$ **then**
        Exploitation: mode with the highest probability
      else
        Exploration: random mode selection
      end if
      Update the association number of CHs
    end for
    Update Local search scheme by Ant k
  end for
  Update pheromone value following
  if Pheromone value $< \tau_{max}$ or $> \tau_{min}$ **then**
    Set pheromone value to τ_{min} or τ_{max}
  end if
end for
Evaluate performance for all schemes by NumAnt Ants, and find the best scheme.

To show the gap between the solution of the sensor association problem obtained by the proposed ACOSA and the optimal solution, a relaxation is given to the problem **P2** as shown in the following equation:

$$\begin{aligned}\mathbf{P2'}: \min_{X} \sum_{i=1}^{I} E_{CMi} + \sum_{j=1}^{J} E_{CMj} \\ = \sum_{i=1}^{I}\left[\frac{1}{\eta}(P_t+\alpha)\cdot M_n \sum_{j}\frac{x_{ij}}{r_{ij}}\right] + \sum_{j=1}^{J}\left[e_c\cdot(M_n\cdot x_{ij}) + E_{DA}\cdot\left(\sum_{i}(M_n\cdot x_{ij})\right)\right]\end{aligned} \tag{23}$$

$$s.t.\ \ (5), (6), \tag{24}$$

$$x_{ij} \in [0,1]. \tag{25}$$

In the relaxed problem, both the objective function and the constraints with respect to the sensor association variables are convex, so that **P2'** is a convex optimization problem. It can be directly solved by the CVX toolbox. The optimal sensor association X is in the range of $[0,1]$, suggesting that one CM can associate multiple CHs. However, it is difficult to achieve "multi-association" in practical systems, which gives the upper bound solution of the sensor association problem. Furthermore, a greedy algorithm with low algorithm complexity is also used to obtain the low bound of the sensor association problem. The greedy algorithm obtains the solution of the problem through a series of local optimum choices, so it is generally not optimal, but can quickly obtain an executable solution at lower algorithmic complexity.

4.2.4. Cluster Head Selection

The consumption of transfer energy is mainly determined by distance between the CHs and CMs. In each cluster, the Euclidean distances between each sensor node to other sensor nodes are calculated first, and then the sum of the distances between each sensor to the other sensors is obtained. The sensor node with the smallest sum distance is selected as the CH, and other sensor nodes in the cluster automatically act as CMs and associate with the CH.

4.3. Overall Algorithm Design

With the algorithm proposed in the above sections, the data collection, sensor association, and CH selection algorithm was detailed in Algorithm 2. At the beginning of the DCTC algorithm, CH selection and sensor association were randomly initialized. After this, the collected data quantity M was optimized with step5–step9 until the sub-gradient algorithm converged to the predetermined accuracy. On the basis of optimal data collection, the suboptimal sensor association was obtained as described in Algorithm 1 (ACOSA). After several iterations, when the BCD algorithm converges, the suboptimal solution of the problem **P** is obtained. Afterwards, the CHs were re-selected according to the results of the sensor association, and when the sensor association and CHs were no longer changed, we thought the entire algorithm converged, and the Data Collection and Topology Control algorithm based on ACO are determined.

Algorithm 2 Data Collection and Topology Control based on ACO (DCTC)

Initialize CHs and user association X^0 randomly.
Initialize $(\lambda, \nu)^1$ and $r_1, r_2, r_3 = 0$.
repeat
    repeat
        repeat
            Update M^{r_1} according to Equation (14).
            Update $(\lambda, \nu)^{r_1+1}$ according to Equations (16) and (17), respectively.
            Update $r_1 = r_1 + 1$.
        until Sub-gradient algorithm converges to a prescribed accuracy.
        Obtain sensor association scheme following Algorithm 1 (ACOSA).
    until BCD method convergences.
    Calculate the sum of Euclidean distances between each sensor and other sensor in the cluster.
    Select the sensor with the smallest distance as the CH.
until Sensor association and CHs no longer change.

5. Experiment Simulation

In this section, N sensor nodes are randomly deployed by Poisson point process (PPP) with a deployment density value of ϕ. This paper compares the proposed algorithm DCTC with the OCM-FCM [30], GREEDY, Relax-CVX and LEACH algorithms proposed in [26]. The simulation parameters in the paper are shown in Table 2.

Table 2. Simulation parameters.

Variable	Parameter	Value
S	Distribution area	500×500
ϕ	Deployment density of WSN nodes	250
$N_j^{\max}$	Maximum access number of CHs	30
σ	Satisfaction coefficient	1×10^3
β	Trade-off parameter	100
w_c	Energy cost for data acquisition	1×10^{-8}
p_t	Data transmission power	20 mW
η	Power amplifier efficiency	0.9
α	Circuit power	5 mW
e_c	Energy consumption for data receiving	5 nJ/bit
E_{DA}	Energy cost for data aggregation	0.5 nJ/bit
$M_{\max}$	Maximum data collection amount	1000 bit

Figure 2 shows the sensor association result with DCTC in this paper. All sensor nodes are randomly deployed at a density of ϕ following the PPP and are divided into two types: CHs and CMs. Each CM is associated with one CH for data transmission. Considering the fact that random deployment will make the density of sensor nodes vary in different regions, and the CH load is higher in regions with high density, which leads to the large energy consumption of the CH. Therefore, it is necessary to limit the maximum number of CH associations. As shown in this figure, the CMs are evenly divided into five clusters, which means that the proposed algorithm can achieve load balancing among different CHs. Although the result is similar to that of previous works in the scenario, the algorithm in this paper is essentially different, which can better improve the energy efficiency and resource utilization of WSNs.

Figure 3 shows the relationship that the objective function values of the algorithm with the number of iterations. We can see the convergence performance of the algorithms in this figure. After six iterations, the objective function values are no longer changes with all three algorithms: GREEDY, DCTC and Relax-CVX, indicating that the algorithms can converge relatively quickly. Moreover, the performance of Relax-CVX outperforms that of the others, but the upper bound can only be achieved with multi-association, which is difficult in practical systems. The performance gap between the DCTC and Relax-CVX is relatively small, which indicates that the approximate solution obtained by DCTC is closer to the optimal solution. This verifies that the proposed DCTC can also obtain a high-quality approximate sub-optimal solution in a heuristic way. GREEDY obtains a feasible solution with the lowest algorithmic complexity, even if the solution has a certain gap from the optimal one.

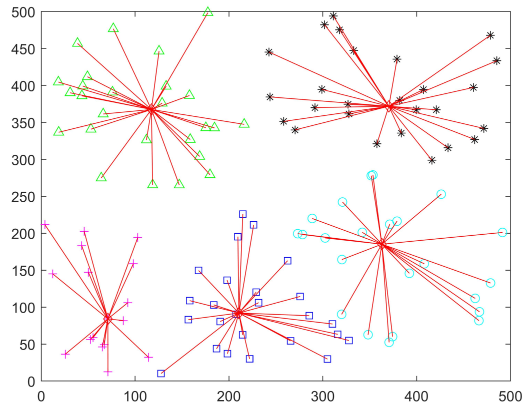

Figure 2. Sensor association result of the proposed algorithm.

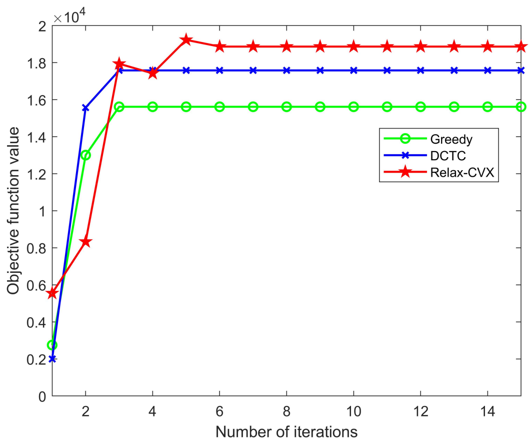

Figure 3. The objective function values versus the number of iterations.

Figure 4 shows the remaining energy of all sensor nodes with the number of rounds. Compared to the LEACH algorithm, all the algorithms used in this paper can effectively reduce the energy consumption and prolong the survival time of the whole WSNs. In this paper, all phases of sensing, including the data collection and transmission stages, were considered, and this paper constructs a joint optimization problem for data collection and sensor association, while also proposing a CH selection algorithm to guarantee the most reasonable CH selection. In addition, sensor association and CH selection were iterated several times to obtain an optimal topology control strategy. For Relax-CVX, it is able to achieve optimal solutions with multi-association in the sensor association problem, and thus has the longest WSN survival time. For DCTC, it has some difference with the results of Relax-CVX in solving the problem, resulting in slightly less survival rounds than that of Relax-CVX, but the gap is only approximately 10 rounds, which means that the proposed algorithm can extend the survival time of WSNs and improve the energy efficiency. Considering the fact that OCM-FCM does not optimize the amount of data collection, only clusters and cluster heads are selected for all sensor nodes and the randomness of the initial cluster head of OCM-FCM will also lead to the difference of clustering results, so the energy consumption of OCM-FCM is higher than GREEDY. LEACH selects and associates CHs in a randomized way and places no limit on the number of CH accesses, which leads to the worst performance of the Leach algorithm.

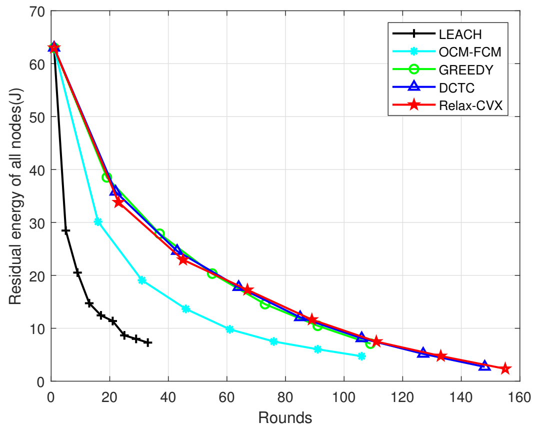

Figure 4. Residual energy of all nodes versus the number of rounds.

Figure 5 shows the number of surviving nodes versus the number of rounds. Relax-CVX still has the best performance. For the proposed algorithm DCTC, the survival sensor node number changes to be almost the same as Relax-CVX, suggesting that the proposed algorithm yields a high-quality sub-optimal solution, and is therefore beneficial for both improving energy utilization efficiency and increasing the number of surviving nodes. Compare with DCTC and Relax-CVX, there is a certain gap of approximately 40 rounds with GREEDY, which ultimately results in the poor performance of the GREEDY-based topological control strategy. The LEACH algorithm may have an excessive number of single CH associations, and the clusters are relatively unreasonable, which makes the sensor nodes die faster.

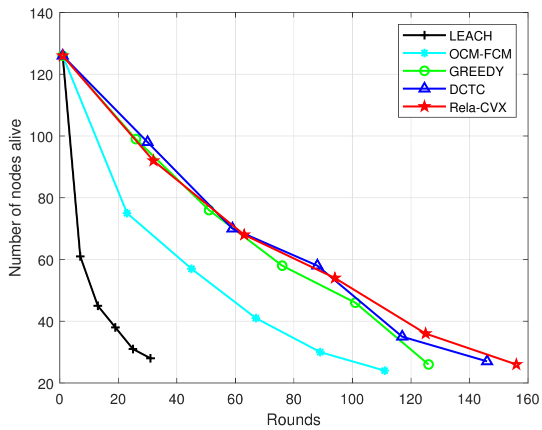

Figure 5. Number of nodes alive versus the number of iteration rounds.

Figure 6 shows the utility of data collection per unit of energy consumption of different algorithms. With the increase in the amount of data collected, the energy consumption will also increase. Therefore, utility per unit of energy was selected as the simulation index in this paper. It can be seen from the figure that, similarly to energy consumption, Relax-CVX is the best, DCTC is the second and GREEDY has a certain gap compared with the other two. For OCM-FCM and LEACH, the optimization of the amount of collected data is not considered, so the amount of collected data is fixed in the simulation of this paper. Compared with LEACH, OCM-FCM has more reasonable clustering results and less energy consumption. Therefore, when the amount of collected data is the same, the utility of OCM-FCM's collected data per unit of energy consumption is higher than that of LEACH.

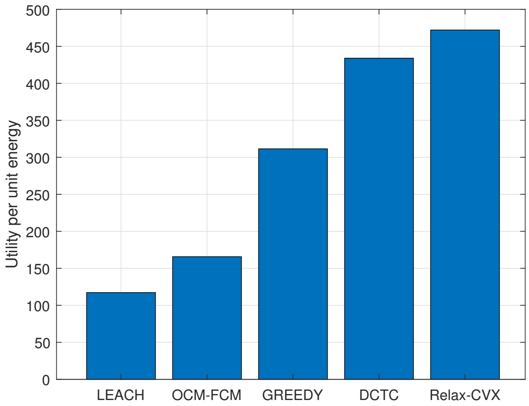

Figure 6. The utility of data collection per unit of energy consumption of different algorithms.

6. Conclusions

The intelligent management of a power materials warehouse requires the collection of information from all parts of the storage system through sensor nodes. In order to improve the energy utilization and monitoring quality of wireless sensor networks, this paper proposed the DCTC algorithm to solve the joint optimization problem on the control of data collection and sensor association, and obtains its suboptimal solution using the BCD method. When solving the Knapsack problem of sensor association, the ACO-based sensor association scheme algorithms (ACOSAs) were proposed, and the GREEDY and Relax-CVX methods were used to show the upper and lower bounds of the optimization problem. Based on the sensor association, CHs were re-selected. Simulation results show that the proposed algorithm, DCTC, can effectively improve the energy utilization and satisfaction of data collection, thus prolonging the lifetime of WSNs. In future work, we will attempt to improve the DCTC by reducing the gap between the suboptimal and optimal solution and reduce its complexity. Furthermore, more practical environments will be considered in the optimization problems.

Author Contributions: Methodology, F.H.; software, G.C.; formal analysis, F.H. and G.C.; investigation, J.Z.; resources, J.X.; data curation, F.H. and J.Z.; writing—original draft preparation, F.H. and G.C.; visualization, F.H.; supervision, S.P.; project administration, J.X.; funding acquisition, S.P. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (62073301) and the Hubei Provincial Natural Science Foundation of China (No.2019CFB347).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

1. Yang, L.; Zheng, Y.; Xu, Y.; Bai, Y. Research on Location Assignment Model of Intelligent Warehouse with RFID and Improved Particle Swarm Optimization Algorithm. In Proceedings of the 2017 International Conference on Computer Systems, Electronics and Control (ICCSEC), Dalian, China, 25–27 December 2017; pp. 1262–1266.
2. Yang, J. Design and Study of Intelligent Warehousing System Based on RFID Technology. In Proceedings of the 2019 International Conference on Intelligent Transportation, Big Data Smart City (ICITBS), Changsha, China, 12–13 January 2019; pp. 393–396. [CrossRef]

3. Lu, X.; Lai, J. Communication Constraints for Distributed Secondary Control of Heterogenous Microgrids: A Survey. *IEEE Trans. Ind. Appl.* **2021**. [CrossRef]
4. Ongaro, F.; Saggini, S.; Mattavelli, P. Li-Ion Battery-Supercapacitor Hybrid Storage System for a Long Lifetime, Photovoltaic-Based Wireless Sensor Network. *IEEE Trans. Power Electron.* **2012**, *27*, 3944–3952. [CrossRef]
5. Xiong, W.; Hu, X.; Jiang, T. Measurement and Characterization of Link Quality for IEEE 802.15.4-Compliant Wireless Sensor Networks in Vehicular Communications. *IEEE Trans. Ind. Inform.* **2016**, *12*, 1702–1713. [CrossRef]
6. Jose, J.; Samhitha, B.K.; Maheswari, M.; Selvi, M.; Mana, S.C. IoT based Smart Warehouse and Crop Monitoring System. In Proceedings of the 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 3–5 June 2021; pp. 473–476.
7. Makwana, N.D.; Kumar, A. Virtual Cluster Head-set based Avalanche Predication in Himalayan region. In Proceedings of the 2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies, Ramanathapuram, India, 8–10 May 2014; pp. 683–687.
8. Zhong, L.; Ge, M.; Zhang, S.; Liu, Y. Rate Aware Fuzzy Clustering and Stable Sensor Association for Load Balancing in WSNs. *IEEE Internet Things J.* **2021**. [CrossRef]
9. Abderrahmane, E.A.; Hajraoui, A. Organized Selection Cluster Head on Fuzzy Low-Energy Adaptive Clustering Hierarchy Protocol in Three-Dimensional Wireless Sensor Networks. *Int. J. Sens. Wirel. Commun. Control.* **2021**, *11*, 362–371.
10. Younis, O.; Fahmy, S. HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. *IEEE Trans. Mob. Comput.* **2004**, *3*, 366–379. [CrossRef]
11. Ye, M.; Li, C.; Chen, G.; Wu, J. EECS: An energy efficient clustering scheme in wireless sensor networks. In Proceedings of the PCCC 2005 24th IEEE International Performance, Computing, and Communications Conference, Phoenix, AZ, USA, 7–9 April 2005; pp. 535–540.
12. Lee, J.S.; Teng, C.L. An Enhanced Hierarchical Clustering Approach for Mobile Sensor Networks Using Fuzzy Inference Systems. *IEEE Internet Things J.* **2017**, *4*, 1095–1103. [CrossRef]
13. Zamini, M.S.; Zare, L. A reward based method to wireless sensor network clustering. In Proceedings of the 2009 International Conference on Application of Information and Communication Technologies, Azerbaijan, Baku, 14–16 October 2009; pp. 1–7.
14. Lee, K.; Lee, J.; Lee, H.; Shin, Y. A Density and Distance based Cluster Head Selection algorithm in Sensor Networks. In Proceedings of the 2010 The 12th International Conference on Advanced Communication Technology (ICACT), Phoenix Park, Korea, 7–10 February 2010; Volume 1, pp. 162–165.
15. Kang, S.H.; Nguyen, T. Distance Based Thresholds for Cluster Head Selection in Wireless Sensor Networks. *IEEE Commun. Lett.* **2012**, *16*, 1396–1399. [CrossRef]
16. Ni, Q.; Pan, Q.; Du, H.; Cao, C.; Zhai, Y. A Novel Cluster Head Selection Algorithm Based on Fuzzy Clustering and Particle Swarm Optimization. *IEEE/ACM Trans. Comput. Biol. Bioinform.* **2017**, *14*, 76–84. [CrossRef] [PubMed]
17. Umbreen, S.; Shehzad, D.; Shafi, N.; Khan, B.; Habib, U. An Energy-Efficient Mobility-Based Cluster Head Selection for Lifetime Enhancement of Wireless Sensor Networks. *IEEE Access* **2020**, *8*, 207779–207793. [CrossRef]
18. Heinzelman, W.; Chandrakasan, A.; Balakrishnan, H. An application-specific protocol architecture for wireless microsensor networks. *IEEE Trans. Wirel. Commun.* **2002**, *1*, 660–670. [CrossRef]
19. Zhao, J.; Erdogan, A. A Novel Self-Organizing Hybrid Network Protocol for Wireless Sensor Networks. In Proceedings of the First NASA/ESA Conference on Adaptive Hardware and Systems (AHS'06), Istanbul, Turkey, 15–18 June 2006; pp. 412–419.
20. Gengsheng, Z.; Xiaohua, L.; Xingming, H.; Weidong, Z. The research of clustering protocol based on chain routing in WSNs. In Proceedings of the 2009 Asia-Pacific Conference on Computational Intelligence and Industrial Applications (PACIIA), Wuhan, China, 28–29 November 2009; Volume 1, pp. 292–295.
21. Allirani, A.; Suganthi, M. An Energy Sorting Protocol with Reduced Energy and Latency for Wireless Sensor Networks. In Proceedings of the 2009 IEEE International Advance Computing Conference, Patiala, India, 6–7 March 2009; pp. 1562–1568.
22. Han, Y.; Li, G.; Xu, R.; Su, J.; Li, J.; Wen, G. Clustering the Wireless Sensor Networks: A Meta-Heuristic Approach. *IEEE Access* **2020**, *8*, 214551–214564. [CrossRef]
23. Lai, J.; Lu, X.; Dong, Z.; Cheng, S. Resilient Distributed Multiagent Control for AC Microgrid Networks Subject to Disturbances. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**. [CrossRef]
24. Chubing, Z.; Ru-jing, H. Optimal Portfolios for DC Pension under the Quadratic Utility Function. In Proceedings of the 2011 International Conference of Information Technology, Computer Engineering and Management Sciences, Nanjing, China, 24–25 September 2011; Volume 1, pp. 297–300.
25. Chang, H.; Chang, K. An investment and consumption problem for quadratic utility function in an incomplete market. In Proceedings of the 2012 24th Chinese Control and Decision Conference (CCDC), Taiyuan, China, 23–25 May 2012; pp. 2039–2042.
26. Heinzelman, W.; Chandrakasan, A.; Balakrishnan, H. Energy-efficient communication protocol for wireless microsensor networks. In Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, Maui, HI, USA, 7 January 2000; Volume 2, p. 10.
27. Ren, J.; Zhang, Y.; Zhang, N.; Zhang, D.; Shen, X. Dynamic Channel Access to Improve Energy Efficiency in Cognitive Radio Sensor Networks. *IEEE Trans. Wirel. Commun.* **2016**, *15*, 3143–3156. [CrossRef]
28. Hong, M.; Razaviyayn, M.; Luo, Z.Q.; Pang, J.S. A Unified Algorithmic Framework for Block-Structured Optimization Involving Big Data: With applications in machine learning and signal processing. *IEEE Signal Process. Mag.* **2016**, *33*, 57–77. [CrossRef]

29. Chen, J.; Wu, H.; Yang, P.; Lyu, F.; Shen, X. Cooperative Edge Caching With Location-Based and Popular Contents for Vehicular Networks. *IEEE Trans. Veh. Technol.* **2020**, *69*, 10291–10305. [CrossRef]
30. Su, S.; Zhao, S. An optimal clustering mechanism based on Fuzzy-C means for wireless sensor networks. *Sustain. Comput. Inform. Syst.* **2017**, *18*, 127–134. [CrossRef]