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Dynamic Spatial-Correlation-Aware Topology Control of Wireless Sensor Networks Using Game Theory

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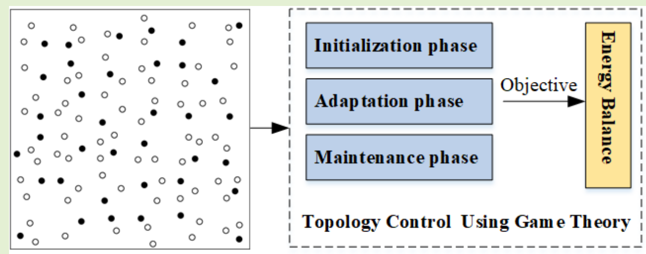
***Abstract*—With the increasing applications of Internet of Things (IoT), service quality becomes more and more important. The topology control of wireless sensor networks (WSN) is one of the key techniques to optimize the quality of service (QoS) of IoT. Game theory is an efficient approach of WSN topology control through global optimization, which resolves the conflicting objectives of self-regard nodes. However, many existing topology control algorithms using game theory waste energy due to the transmission of redundant sensed data. In this study, we present a novel dynamic spatial-correlation-aware topology control method (TC-GSC) using game theory to reduce the redundant data. In TC-GSC, the monitoring region is divided into several spatial-correlation areas, and only one active node is periodically selected for each area. Based on the collected information of active nodes, the sink node computes the transmitting power level using game theory and generates the connected topology. Moreover, the WSN topology can be dynamically updated when the active node's remaining energy becomes greatly uneven, or the active node's working time exceeds the threshold. Extensive simulation results demonstrate that TC-GSC can effectively improve the energy balance of nodes and significantly reduce the energy waste, thus prolonging the lifetime of networks.**



***Index Terms*—Wireless sensor network, topology control, energy balance, spatial correlation, game theory.**

I. INTRODUCTION

INTERNET of Things supported by wireless sensor networks (WSNs) is an attractive and flexible option to be applied to many real-world scenarios, such as environment monitoring [1]–[3], target tracking [4], [5], military mission [6] and volcanic monitoring [7]. Efficient and balanced energy use is a challenge to extend the lifetime of WSNs since sensors are typically powered by batteries. Here topology control (TC) is a technique that enables the network to have an optimal performance by scheduling the transmitting power of each node. To keep even residual energy among all sensor nodes and extend the network lifetime while maintaining connectivity, sensor nodes select the transmitting power level and form the network topology. However, since the existence of self-regard nodes, their actions are only to optimize their own objectives [8], which poses a challenge to topology control. For example, if a sensor node's energy level is too low, and we only can set a very low transmitting power level at which this node may not communicate with the closest neighbor nodes. In reverse, if we set a very high transmitting power level, the interference will increase among the nodes and accelerate their energy consumption.

For the limited battery capacity of sensor nodes [9], [10], improving the energy efficiency of the WSNs has become a critical issue [11]–[14]. This study aims to balance the energy dissipation over the whole network using TC to prolong the lifetime of WSNs. The dynamic network topology is constructed by satisfying the following global

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objectives: 1) balancing the nodes' energy consumption and improving the network's energy efficiency; 2) maintaining network connectivity.

Most studies on WSNs assume that cooperation among nodes is just to construct a network with good performance. However, it is hard to prove whether this cooperative assumption is reasonable since the actual situation is that nodes either contend for network resources or protect their limited resources [8]. Therefore, nodes would exhibit exactly the opposite behavior: to save their resources and perform their self-interesting behaviors. Because of the selfishness of nodes, the interaction among nodes is modeled as a game, and the TC can be analyzed as a non-cooperative game. Game theory is an effective method to analyze the existence of objective conflicts in selfish nodes, thus achieving efficient and interconnected networks [15]–[17]. Moreover, the most energy consumption of nodes is concentrated on the transmission of information. In particular, in a WSN with high density, the nodes that are close to each other tend to collect similar measurements. The redundant information exchange may excessively waste the limited energy of nodes [18], [19]. We go further and consider spatial-correlation into TC problem to reduce the redundant information transmission. A selected node can report the event information representing all the nodes within a given spatial-correlation area, reducing the energy loss caused by the redundant data transmission.

In this study, the monitoring area is partitioned into several correlation regions, and then each correlation region selects one node as an active node. Then, each active node can calculate its transmitting power level and generate a connected topology based on game theory. When the energy consumption among network nodes becomes uneven, the active nodes will be reselected and the network topology will be updated to maintain the energy balance.

The main contributions of this article are as follows.

- A new spatial correlation aware topology control method (TC-GSC) using game theory is proposed. TC-GSC can greatly balance the nodes' energy dissipation and extend the lifetime of WSNs compared with the existing algorithms.
- We enable the topology in TC-GSC dynamically updated. Each node can calculate its transmitting power level based on game theory and generate a connected topology. The topology is dynamically updated when the remaining energy of each sensor node becomes greatly uneven, or the next round is coming.

The rest of this article is shown below. In section II, the related work is reviewed and summarized. Then, some key concepts and the problem model are described in Section III. Section IV gives a detailed introduction about TC-GSC method. In section V, simulation results verify the effectiveness of the proposed method. In the end, we summarize this study in Section VI.

II. Related Work

There are many existing approaches for resolving the TC problem in WSNs. We can find comprehensive surveys of TC in [20] and [21]. Üster and Lin [22] proposed a new TC approach by limiting the available energy of the sensor to a small part of the total available energy. Two types of solution representation, multi-neighborhood combination, and cut set inequality based on target value, are used to improve the evaluation of candidate solutions. Liu *et al.* [23] presented a new opportunity-based TC approach and proved that it was NP-hard. Using reliability theory, they presented a fully distributed algorithm named CONREAP, and CONREAP can ensure the accessibility of the network. Cuzzocrea *et al.* [24] designed a novel weighted bi-directional TC algorithm called edge betweenness centrality (EBC). EBC can help identify different roles (such as proxies and outliers) in WSNs by evaluating the relationships among network entities to achieve high-quality service (QoS). Lin *et al.* [25] proposed a lightweight algorithm ATPC for adaptive transmitting power control in WSNs. The study provides a valuable future research direction. Zhao and Guo [26] proposed an improved algorithm based on an energy-saving clustering algorithm (CAEC). The algorithm changes the cluster area and performs communication stability by selecting a cluster head node. Similarly, based on the idea of clustering network, Chang *et al.* [27] presented an unsupervised learning approach for TC to prolong the lifetime of ultra-dense wireless sensor networks by balancing energy consumption. However, both [26] and [27] fail to consider the dynamic variability of the sensor network. Several methods have been proposed in [28]–[31] to extend the network lifetime by improving node energy efficiency. However, these approaches rely on the basic assumption that nodes have a social responsibility and cooperate in good faith to achieve the expected global goals. Actually, in pursuit of maximizing utility, nodes in the network can be selfish and perhaps at the sacrifice of another nodes' utility.

The game theoretical model has been adapted to describe the scenarios of cooperation and competition among rational decision-makers [32]. Eidenbenz *et al.* [33] firstly proposed a solution to the TC problem with nodes as selfish states. They proposed three games and studied their connectivity, but they did not guarantee the game would reach the state of Nash Equilibrium (NE). In [8] and [28], the theoretical analysis of game-based TC algorithms was provided. The TC problem's main idea was modeled to be a non-cooperative game to investigate the connectivity [34]. Komali *et al.* [8] proposed a δ-improvement algorithm (DIA), which converges to the energy-saving topology and the steady-state power allocation vector. Tan *et al.* [35] used a game-based method to evaluate each node's energy state and acquisition ability, making the topology efficient and reliable. Nahir *et al.* [36] studied the performance of non-cooperative networks from the consideration of three topology designs: link cost, path delay and path congestion. The existing TC algorithms are dependent on global information of nodes, which results in energy waste. Hao *et al.* [37] proposed a distributed TC algorithm based on virtual game-based (VGEB), where each node only needed to exchange information once. Therefore, their algorithms can greatly reduce energy consumption. Xu *et al.* [38] proposed a distributed TC algorithm with life extension (TCLE) to construct a dynamic network topology and extend its lifetime.

Hao *et al*. [39] present a novel Markov lifetime prediction model (MLPM) for each node to forecast their lifetime. Based on MLPM, they proposed a distributed TC game algorithm for WSN by making use of the best response strategy. However, the real-time prediction of node lifetime of each node may lead to more energy consumption. Du *et al*. [40] proposed a game-based TC algorithm to balance energy among nodes. By introducing the Theil index, they also designed an improved optimization-integrated utility function. In their TC process, the redundant information exchange may increase the consumption of nodes' energy.

In general, the effects of existing TC algorithms are limited to assign the node to transmitting power level by game-based TC algorithms to achieve energy efficiency. Considering that large-scaled dense WSNs are increasingly deployed in various applications and close nodes tend to collect similar data, we can utilize the spatial correlation to help reduce redundant data transmission. In application-specific sensor networks, many strategies help maximize energy savings [41]–[45]. Villas *et al*. [46] presented a dynamic and scalable spatially correlated tree algorithm (YEAST). Under the action of YEAST, about 75 percent of nodes' remaining energy can be stored in the area.

III. Preliminaries and Dynamic Topology Control

In this section, we present preliminary knowledge of game theory and provide a network model considering spatial correlation. Then, we use the game model to describe the dynamic TC process based on active node selection.

A. Preliminaries

1) Game Theory: Game theory is a set of models and mathematical tools used to analyze interactive decision processes [41], [42]. The non-cooperative model deals with the interactions among individual decision-makers [38]. Such a model is called a game, and the decision-maker is called a player.

Definition 1 [8]: A strategic non-cooperative game $\Gamma = <B, S, u>$ consists of three elements:

(i). Player set B: $B = \{b_1, b_2, \ldots, b_n\}$, where n is the number of players in the game.

(ii). Strategy set S: $s \in S = \times_{i=1}^{n} S_i$, where S denotes the Cartesian product of i-th player's action and $s_i \in S_i$ is the i-th player's strategy over the set of its possible strategies S_i. Often, we denote a strategy profile s $= (s_i, s_{-i})$, where s_i is the i-th player's strategy, and s_{-i} denotes the strategy of the other n - 1 players.

(iii). For each player $b_i \in B$, utility function u_i: $S \to R$ models the player's preferences over strategy profiles. $U = \{u_1, u_2, \ldots, u_n\}$: $S \to R$ denotes the vector of such utility functions.

Nash equilibrium (NE) is an important concept in the game theory of non-cooperative strategy [47]. It is a stable solution of the game in which no player may actively deviate from his current strategy choice.

2) Wireless Sensor Network Modeling: For our analysis, the network is represented as a connected undirected graph $H = (N, E)$, where $N = \{n_1, n_2, \ldots, n_n\}$ is the node set, and E is the edge set for the communication links among these nodes. Further explanation, we define E as below:

$$E = \{e_{mn} p_m >= \omega_{mn}\} \tag{1}$$

where p_m represents the m-th node's transmitting power and ω_{mn} defines the transmitting power required to establish a link between node m and node n. Each node can select the optimal transmit power and select a group of neighbors using an adjustable power model. When node m transmits the data packet at $p_m \in [0, p_m^{\max}]$, and node n receives the packet at the power level greater than a common signal capture threshold $\tilde{p}$, the data packet can be detected and decoded correctly.

$$p_m \cdot G_{mn} \geq \tilde{p} \tag{2}$$

where G_{mn} is the propagation factor [38]. In the free space propagation model, G_{mn} satisfies:

$$G_{mn} = C d_{mn}^{-\alpha} \tag{3}$$

where C is a constant, α represents the path loss factor and satisfies $2 \leq \alpha \leq 6$, and d_{mn} denotes the Euclidean distance from node m to node n. All links in graph H are bi-directional, and we define a link state variable l_{mn} for each node m given by (4):

$$l_{mn} = \begin{cases} 1 & p_m \geq \omega_{mn} \\ 0 & otherwise \end{cases} \tag{4}$$

A bidirectional link $l_{mn} \in H$ between node m and n exists if and only if

$$\min\{p_m, p_n\} \geq p^{th}/G_{mn} \tag{5}$$

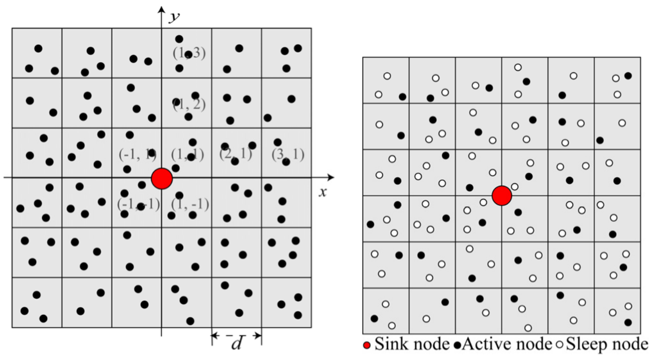
Based on (4) and (5), we obtain $\omega_{mn} = p^{th}/G_{mn}$. More precisely, we assume that $\{\forall m, n | \omega_{mn} = \omega_{nm}\}$. Let $NH_n(p_m) = \{j | l_{mn}(p_m) \cdot l_{nm}(p_m) = 1\}$ denote the neighbor set of node m. The joint transmitting power profile $p = (p_1, \ldots, p_n)$ generates a network, defined as

$$g(p) = \{mn | l_{mn}(p_m) \cdot l_{nm}(p_n) = 1; m \neq n \in N\} \tag{6}$$

Let $g(p)$ denote the above network. If node m transmits a data packet at $p_m^{\max}$, the connected graph g_{max} with maximum transmitting power will be generated. The goal of TC-GSC is to obtain a subgraph $g(p)$ of g_{max}, which is energy-saving while preserving the connectivity of the network.

3) Spatial Correlation: In this article, all sensor nodes are randomly deployed in a 2D plane and formed a homogeneous network. Besides, a sink node is deployed in the center of the area. We assume that the sink node is used as the central controller, responsible for collecting information from regular nodes and returning the results to them. Nodes that are close in space tend to collect similar values. It is more efficient to arrange sensor nodes in the same group to collect their sensing data alternately than to have all nodes in the same group collect measurements simultaneously [42].

We divide the deployment area of sensor nodes into many rectangle cells. Each cell represents a correlation area and its



(a) (b)

Fig. 1. Spatial correlation (a). Correlation region; (b) Selection of active node.

size is denoted as d. It is important to point out that the maximum size d_{max} of a cell is the length of the triangle's leg in a right triangle since r_c is the hypotenuse ($d_{max} = r_c \cos 45°$), where r_c is the communication radius of nodes. The size d of a cell can be adjusted according to the specific application and event type. The ordered pair (x_c, y_c) represents a cell, as depicted in Fig.1 (a). To save energy and extend the lifetime of the network, nodes in the same correlation region are arranged for alternating to collect sensing data.

The sink node calculates the correlation region to which each node belongs based on global geographic information and cell size d. Specifically, (x_c, y_c) denotes the coordinates of the cell that the node belongs to, (x_n, y_n) represent the coordinates of the node and (x_s, y_s) denotes the coordinates of the sink node. First, the value of x_c is initialized to 0. Then, if the coordinate x_n of node n is greater than 0, it will check if it is divided into any cell to the right of the sink node by calculating the value of x_c; otherwise, node n will check if it is divided into any cell to the left of the sink node. The specific calculation of x_c is as shown in (7):

$$x_c = \begin{cases} \left\lfloor \dfrac{(x_n - x_s) - d/2}{d} \right\rfloor + 1 & x_n > 0 \\ \left\lfloor \dfrac{(x_n - x_s) + d/2}{d} \right\rfloor - 1 & x_n < 0. \end{cases} \tag{7}$$

Moreover, the value of y_c can be computed according to the same steps as above.

B. Dynamic Topology Control

1) Selection of Active Node: Assume that each correlation region $cell = \{1, 2, \ldots\}$ selects only one sensor node to be active, and the other nodes are in sleep state at time t, as depicted in Fig.1 (b). The active nodes of all correlation regions form an active node set $A = \{a_1, a_2, \ldots, a_m\}$, $m < n$, and m denotes the number of correlation regions of the deployment area. As a control center, the sink node masters the information $I_n = < (x_n, y_n), s_n >$ of all each node, s_n denotes the node's status information including residual energy and whether it is good or not. In the first round of selection, the sink node selects the nearest node in each correlation region as the active node set. Except for the first round of selection, for each remaining round of selection, the sink node broadcasts a validation message to each node: (i) if the node receives a validation message, it indicates that the node is good, and the state of node will be set as GD. Also, its idle time threshold $\tilde{T}$ will be added into its state information s according to (8).

$$\tilde{T} = \gamma \exp(V_{sta}/V_{pre}). \tag{8}$$

Here, γ can be chosen as we wish. V_{sta} is the standard working voltage of the battery, and V_{pre} represents the current-voltage of the battery [48]. Then, the node will return its information I_n to the sink node; (ii) Otherwise, if the sink node does not receive any return message from the node, it represents that the node is faulty and its state will be set as FT. Finally, the sink node will make a decision based on the status information returned by nodes, and the node with the highest residual energy level will be selected as the active node of its correlation region. Besides, the sink node returns the selection result of the active node updated in each correlation region to all nodes.

2) Game Model for Topology Control: We get the active node set A after selection, and the topology is dynamic because A is changing. In this article, the TC process is based on the optimization of transmitting power of the active node set. Here, we use a game model to explain the TC process:

(i). The player set $B = \{b_1, b_2, \ldots, b_m\}$, $m < n$ denotes the selected active nodes, and each node can adapt its transmitting power $p_i \in [0, p_i^{\max}]$.

(ii). The power vector $p = (p_1, p_2, \ldots, p_m)$ consists of individual transmitting power levels, thus forming a strategy space S.

(iii). Each node weighs the benefits it receives from the topology $g(p)$ and the price of constructing $g(p)$. Considering the connectivity, transmitting power level and energy efficiency, we employ the utility function to map the power level vector to each node's benefit. For each node $k \in N$ at time t, $p_k(t)$ represents the transmitting power of node k and $p_{-k}(t)$ represents the transmitting power of other nodes except node k. The utility function is defined as:

$$u_k(p_k(t), p_{-k}(t)) = f_k(p_k(t), p_{-k}(t)) \cdot (f_e(k) + f_{pr}(k)) - c_k(p_k(t)), \tag{9}$$

Here, $f_k\ (p_k(t), p_{-k}(t)) = 1$ or 0, and $f_k\ (p_k(t), p_{-k}(t)) = 1$ means that node k can establish connections with its neighbor nodes, and the connected path is composed of bi-directional links, and the power level of these links should be less than $p_k(t)$; otherwise, $f_k\ (p_k(t), p_{-k}(t)) = 0$. Obviously, $f_k\ (p_k(t), p_{-k}(t))$ is non-decreasing, i.e., $f_j\ (p_k(t), p_{-k}(t)) \geq f_j\ (q_k(t), q_{-k}(t))$, if $p_k(t) > q_k(t)$, $\forall j \in N$. $f_e\ (k)$ represents the energy-balance benefit from the topology $g(p_k)$ and $f_{pr}(k)$ represents the contribution to form the connected topology, which are expressed in (10) and (11).

$$f_e(k) = \frac{\alpha \cdot \sum (E_r(k) - \overline{E_r^h})^2}{\sum NH_k^h}, \tag{10}$$

$$f_{pr}(k) = \beta \sum NH_k^h. \tag{11}$$

Here, $E_r(k)$ represents the residual energy and $\overline{E_r^h}$ denotes the average residual energy of node k's h-hop neighbor nodes. NH_k^h represents the number of h-hop neighbors of node k. The benefit multiplier $(f_e\ (k) + f_{pr}\ (k))$ represents the value that each node contributes when it connects to other nodes. Additionally, α and β are a pair of parameters that make $(f_e\ (k)+f_{pr}\ (k))$ larger than $c_k(p_k(t))$ when $f_k\ (p_k(t), p_{-k}(t)) = 1$. However, due to the energy cost, nodes are reluctant to contribute to the network's evolution. Intuitively, the higher transmitting power $p_k(t)$ results in fast energy dissipation. The lower the residual energy $E_r(k)$, the less likely node k is to deplete its valuable energy resources. We assume that the cost of node k is an increasing function of its residual energy $E_r(k)$, which is conceived by (12).

$$c_k(p_k(t)) = u \int_{E_0(k)-E_r(k)}^{E_0(k)-E_r(k)+p_k(t)\cdot T} g(x)dx. \tag{12}$$

Here, $E_0(k)$ represents node k' s initial energy, T denotes the unit transmission time satisfying $p_k(t) \cdot T \leq E_r(k)$, and u is the sufficient small so that $c_k(p_k(t)) \in [0, 1]$. The increment function $g(x)$ denotes the energy-cost function, and it represents the cost of using x units of energy. Referred to [38], $g(x)$ is define as $exp\ (x/10)$.

In conclusion, we define the above game model to describe the process of dynamic TC. The main purpose is to force each active node to select the transmitting power based on the utility function u (defined in (9)) to make the topology reach the NE state. The specific solution will be explained in the next section.

IV. Dynamic Spatial-Correlation-Aware Topology Control by Game Theory

In this section, a dynamic spatial-correlation-aware topology control algorithm (TC-GSC) using game theory for WSN is proposed. The TC-GSC consists of three phases, i.e., initialization, adaptation and maintenance.

A. Initialization Phase

Each node i belonging to active nodes set A initializes its power level to $p_i^{\max}$. To discover its neighbors, each node broadcasts Neighbor Request Message (NBM) at $p_i^{\max}$ with h-hop value (mark $= h$) and collects the responses provided by $p_j^{\max}$. The format of the NBM is [NBM, ID_i, (x_i, y_i), $p_i^{\max}$, $E_0(i)$, $E_r(i)$, T]. Upon successful reception of Neighbor Reply Message (NRM) from each responding neighbor j, the node i adds a message of the neighbor j to its neighbor list, marked as NH_i^1. The format of the NRM from node j to i is [NRM, ID_j, (x_j, y_j), p_{ij}, $E_0(j)$, $E_r(j)$, T]. Next, node j continues to broadcast NRM to others, whose mark has been changed. Until the mark reduced to 0, the h-hop neighbor nodes of node i can be obtained, marked as NH_i^h, the connected local topology is $G_i^{\max}$.

B. Adaptation Phase

The transmitting power of node i depends on the node degree, residual energy and topology related information collected during the initialization phase. For each node i, we discretize its strategy set S into a descending order set:

$$S_i = \{p_i^{\max} = p_i^1, p_i^2, \cdots, p_i^{\eta} = p_i^{\min}\} \tag{13}$$

Algorithm 1 Game $\Gamma(i)$

1: **Input:** the neighbor list of the node i: NH_i^1; the neighbor list of i-th node's h-hop neighbor: NH_i^h.
2: **Output:** the i-th node's transmitting power p_i
3: $l = 1$
4: $p_i = p_i^{\max} = p_{jl}^{(i)} \in p_i$
5: **while** p_i is not a NE **do**
6: $l = l + 1$
7: choose $\hat{p}^{(i)} = p_{jl}^{(i)} \in p_i$
8: **for** all $j \in A(i)$ **do**
9: **if** G_i^h is connected then
10: $u_j(i) = u_{jl}(i)$
11: **else do**
12: $u_j(i) = -c(i)$
13: **end if**
14: $\hat{p}_i = \arg\max_{q_i \in \{(p_{ik}, p_{i(k+a)})\}} u_i(q_i, p_{-i})$
15: **end for**
16: **end while**

We select enough small step size δ from p_i^m to p_i^{m+1} such that at most one link will be deleted. In the game process, each node $i \in A$ selects the transmitting power one less than its current level if the selected power level leads to a high payoff than its current power level; otherwise, it reverts to the power level it was currently transmitting at [49]. Besides, p_{ik} is the i-th node's current transmitting power level, $k = 1, 2, \ldots, \eta - 1, k < k + a \leq \eta$. Each node selects the next transmitting power level given by:

$$\hat{p}_i = \arg\max_{q_i \in \{(p_{ik}, p_{i(k+a)})\}} u_i(q_i, p_{-i}) \tag{14}$$

Algorithm 1 formalizes the procedure of the power adaptation phase. For each node i, all its neighbor nodes have an opportunity to update their power level (Line 3). If the transmitting power of node i cannot make the current game process reach the NE, it will reselect the transmitting power that satisfies (14) until the NE is reached (Line 4 to 16). Without dropping the connectivity of local topology g_i, if any node's power level is not selected to reduce its transmitting power further, the algorithm will be terminated. Moreover, node i needs to update its local topology g_i based on the neighbor's new transmitting power level settings. When node i receives NRM message from neighbor j, it will check if there exists a path between them in which all the intermediate nodes belong to the i-th node's neighbor set, and node i will update its neighbor set $NH(i)$ according to the j-th neighbor's new power setting. Otherwise, node i will delete neighbor j from its neighbor set $NH(i)$.

C. Maintenance Phase

The number of times the topology adaptively reconfigures is defined as the control time of the topology, denoted as TC(t). Its unit is the round of the algorithm as abbreviated as r. In the beginning, the energy of each node i at TC$(t) = 0(r)$ is $E_0(i)$. According to Algorithm 1, all nodes execute the power level adaptation for the first time (TC$(t) = 1(r)$) and $\hat{p}(t_1)$

represents the NE. Then, $\hat{p}(t_1)$ induces an energy-balanced network topology. However, the energy nodes may become gradually unbalanced as time passes. Therefore, we propose two triggered scenarios where the network topology can be adaptively reconfigured during the topology maintenance phase. When the i-th active node's residual energy $E_r(i)$ is smaller than the threshold energy $\tilde{E}(i)$ or time t_i exceeds its active time threshold $\widetilde{T}(i)$ (See (8)), all sleep nodes in the i-th node's spatial correlation region $cell_i$ will receive the Awake Request Message (ARM) from node i, and the node whose residual energy level is highest will be triggered to become the active node. Each time the topology is updated, the TC time TC(t) will increase by one.

In this article, we pre-set the maximum TC(t) to TC$(t)_{\max}$. In general, the proposed TC-GSC algorithm can be summarized as follows:

- Step1: Partitioning of correlation region.
- Step2: Forming a set of active nodes A. Each node i in A, calculate its active time threshold $\tilde{t}(i)$. If TC$(t) = 1(r)$, go to Step 3, else go to Step 4.
- Step3: Initializing the network topology.
- Step4: Each node adapts its power level and then updates network topology.
- Step5: When the residual energy of node i is smaller than $\tilde{E}(i)$, it will trigger other nodes in its correlation area within $\tilde{t}(i)$.
- Step6: As time elapses to reach $\tilde{t}(i)$, it will trigger other nodes in its correlation area.
- Step7: Repeating Step 2 to Step 6 until TC(t) = $TC(t)_{\max}$.

D. Complexity Analysis of TC-GSC

Theorem 2: For the TC game given by Γ $<A, S, u>$, the complexity of the TC-GSC algorithm is O($m \times$ TC$(t)_{\max}$), where m is the active node number and TC$(t)_{\max}$ is the maximum time of TC.

Proof: As shown in the steps of TC-GSC algorithm, the main calculation is concentrated on Algorithm 1 in step 4. According to Algorithm 1, each node's best result is to select the minimum power level needed to maintain network connectivity. In this case, none of the nodes can reduce the power to a lower level, but the maximum utility is still available. At the end of the first round, each node's utility is given by (7). In the second round, no node may select a transmitting power level $p_i < p_i^*$ and still maintain connected. Thus, after m iterations, Algorithm 1 converges to NE given by $p^* = \{(p_1^*, p_2^*, \cdots, p_m^*)\}$. Also, from TC-GSC algorithm, we know that the topology will be reconfigured adaptively over time, and the maximum control time is denoted as TC(t)$_{\max}$, so the complexity of the TC-GSC algorithm is O($m \times$ TC$(t)_{\max}$).

V. Experimental Study

We evaluate the performance of TC-GSC, compared with existing game-based TC algorithms, including DIA [8], TCLE [38] and VGEB [37]. We performed simulation experiments with Matlab 2017b. Sensor nodes were randomly deployed in a 500×500 (m^2) area, and the minimum power p_{ij} can be described as (15) [50].

$$p_{ij} = \frac{p_{th}(4\pi)^2 d_{ij}^2 L}{G_{tr} G_{re} \lambda_0^2}. \tag{15}$$

TABLE I
Simulation Parameters

Parameter	Values
Deployment area	500×500 (m^2)
Number of nodes, N	40, 60, 80, 100, 120, 140, 160, 180, 200
Initial energy, E_0	50 (J)
Power threshold, P_{th}	7×10^{-10} (w)
Wavelength, λ_0	0.1224 (m)
Antenna gain of the transmitter, G_{tr}	1
Antenna gain of the receiver, G_{re}	1
Standard working voltage of the battery, V_{sta}	3.6 (V)
Current-voltage of the battery, V_{pre}	[2.8, 4.2] (V)
System loss, L	1
Communication radius, r_c	150 (m)

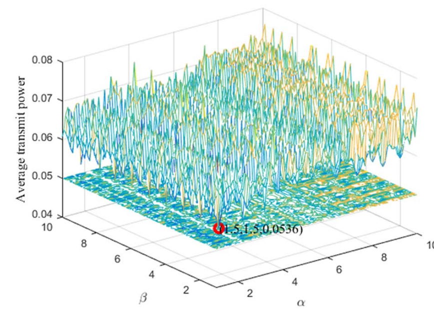


Fig. 2. Optimal parameters α and β.

The parameter γ in (8) is set to 5 and the current-voltage V_{pre} of the battery of each sensor node is selected from [2.8, 4.2]. Table I lists the simulation parameters.

In this article, we carried out four experiments. In the first experiment, the parameters α and β are determined. Then, the node number is set to 40 to 200 with an interval of 20. The performance of the algorithms depends on five indices: node degree, average transmitting power, the variance of residual energy, average hop number of the shortest path and network lifetime. Thirdly, the comparative experiment of algorithm performance versus time is carried out, and the evaluation indices include node degree, average transmit power and average hop number of the shortest path. In the final experiment, we compare TC-GSC with the other three algorithms in terms of residual energy distribution.

A. Determination of Optimal Parameters α and β

From the utility function shown in (9), given $u = 1$, the parameters α and β need to be determined before other simulations because we should consider their impact on the performance of network topology. We deployed 200 nodes in the area randomly, both TC-GSC and other comparative algorithms employed the minimum energy routing for packets transmissions. Grid search, as an effective parameter optimization method, has been successfully applied to many

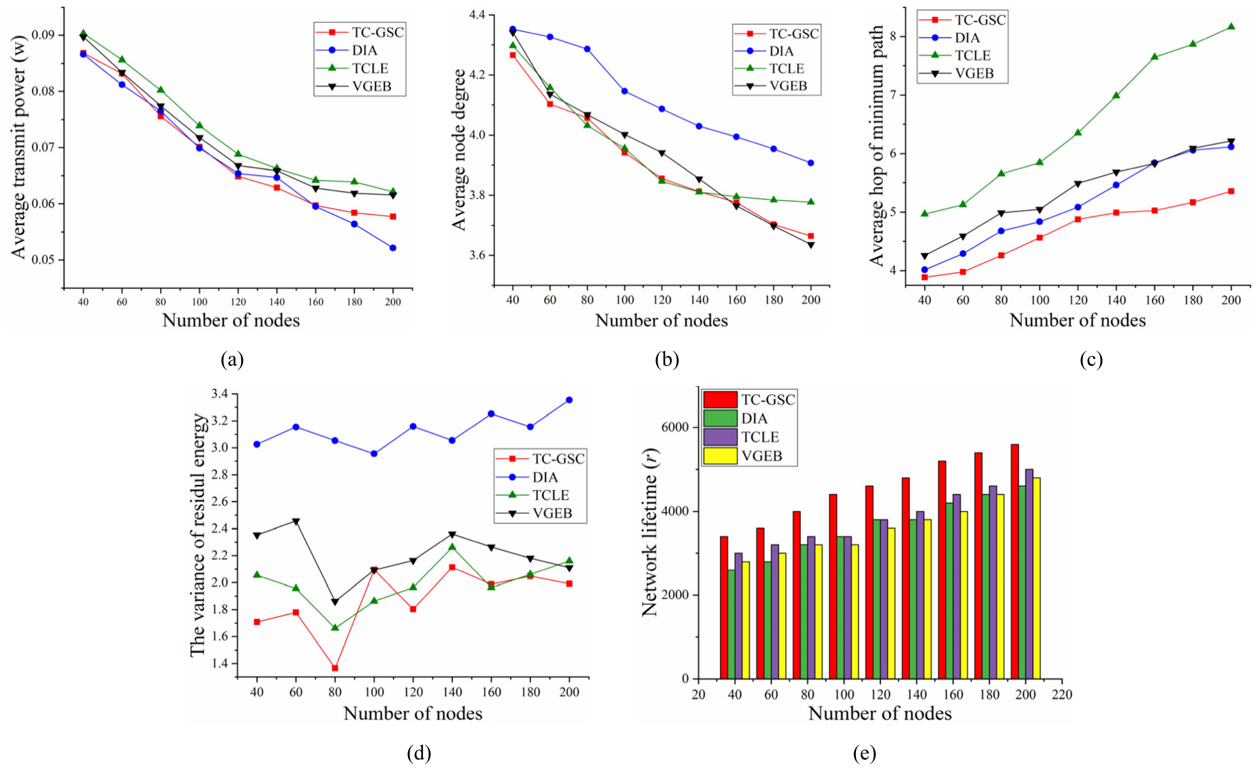


Fig. 3. Network performance vs. number of nodes. (a) Average transmit power; (b) Average node degree; (c) Average hop number of the shortest path; (d) The variance of residual energy; (e) Network lifetime.

TABLE II
AVERAGE TRANSMIT POWER VS. TIME

Algorithm	Time (*r*)									
	200	**600**	**1000**	**1400**	**1800**	**2200**	**2600**	**3000**	**3400**	**3800**
TC_GSC	0.0536	0.0542	0.0552	0.0568	0.0555	0.0565	0.0568	0.0542	0.0554	0.0577
DIA	0.0524	0.0542	0.0530	0.0552	0.0538	0.0548	0.0518	0.0554	0.0542	0.0526
TCLE	0.0542	0.0562	0.0610	0.0628	0.0638	0.0618	0.0637	0.0640	0.0612	0.0622
VGEB	0.0558	0.0532	0.0563	0.0578	0.0568	0.0588	0.0607	0.0594	0.0580	0.0601

TABLE III
AVERAGE NODE DEGREE VS. TIME

Algorithm	Time (*r*)									
	200	**600**	**1000**	**1400**	**1800**	**2200**	**2600**	**3000**	**3400**	**3800**
TC_GSC	3.1529	3.3294	3.5058	3.5294	3.3647	3.4235	3.5364	3.4123	3.3470	3.6647
DIA	3.5348	3.5346	3.7853	3.5116	3.3230	3.5114	4.0232	3.9767	3.581	3.9069
TCLE	3.5581	3.1836	3.6511	3.0232	3.6767	3.7230	3.5462	3.2325	3.7830	3.7767
VGEB	3.5421	3.6186	3.6911	3.4832	3.5467	3.5830	3.6862	3.7525	3.4530	3.6367

algorithms. Therefore, we used grid search to determine the values of α and β. We used the average transmitting power as the only evaluation index of this experiment. To make the value of utility function always be greater than 0, let $\alpha \geq 1$ and $\beta \geq 1$. As shown in Fig.2, α and $\beta \in [1, 10]$, the average transmitting power of nodes reaches the minimum when $\alpha = 1.5$ and $\beta = 1.5$, which means the network topology under this scenario can be energy-saving due to the low average transmitting power. Hence, in the following simulations, we set $\alpha = 1.5$, $\beta = 1.5$.

B. Performance Versus the Numbers of Sensor Nodes

The number of nodes varied from 40 to 200 to change the size of the region. Besides, the network lifetime is defined as the time until the first node exhausts its energy [51]. Fig.3 (a) illustrates that the average transmitting power of the four algorithms gradually decreases with the increasing of the node number. Clearly, the average transmitting power of TC-GSC is slightly higher than that of DIA but lower than that of TCLE and VGEB. As shown in Fig.3 (b), the node degree of TC-GSC is less than TCLE and VGEB, and the node degree of DIA is much more than the other three algorithms. The average hop number of the shortest path of TC-GSC is less than that of other algorithms, as shown in Fig.3 (c), which indicates TC-GSC has excellent real-time property and uses less transmitting power. Fig.3 (d) shows that the variance of residual energy of all nodes under four algorithms. The smaller the variance value is, the evener the residual energy distribution is. From Fig.3 (d), we know that TC-GSC performs best in balancing the energy consumption,

TABLE IV
AVERAGE HOP NUMBER OF THE SHORTEST PATH VS. TIME

Algorithm	Time (*r*)									
	200	**600**	**1000**	**1400**	**1800**	**2200**	**2600**	**3000**	**3400**	**3800**
TC_GSC	5.9520	5.0850	5.1530	4.6222	4.7630	5.3580	5.0326	5.5866	5.2562	5.3552
DIA	6.1542	5.8522	5.6620	6.8622	5.9682	6.2681	5.9635	6.0641	5.1620	6.1160
TCLE	7.0542	8.9562	7.6610	8.8628	7.9638	8.2618	7.9527	8.0604	7.1612	8.1621
VGEB	6.1142	5.9922	6.3820	6.6721	6.2683	6.4884	6.0635	6.0041	5.8620	6.2161

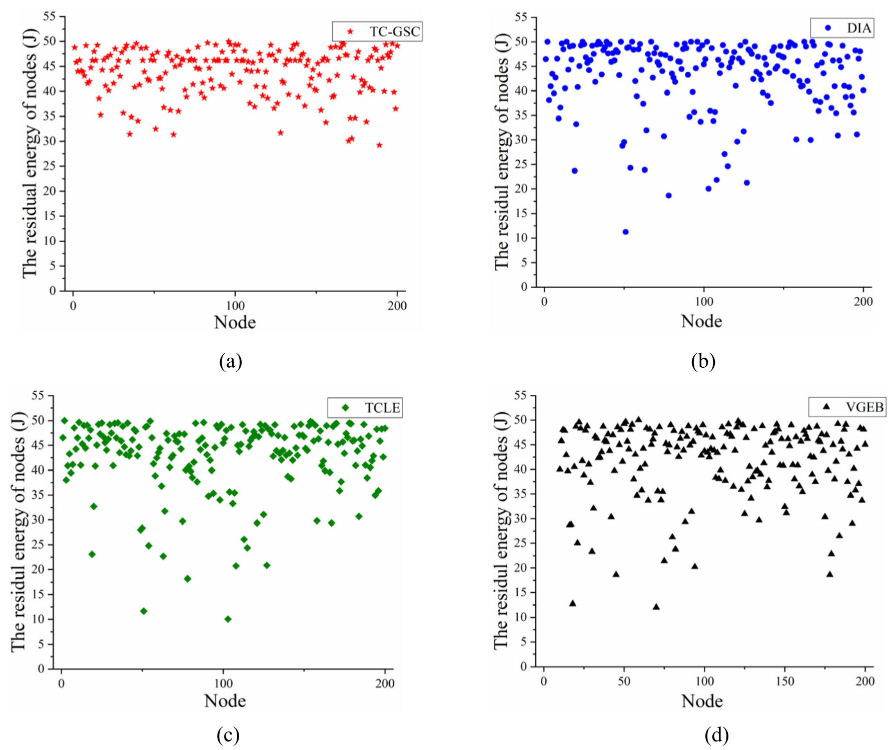


Fig. 4. Performance evaluation in terms of residual energy. (a) TC-GSC; (b) DIA; (c) TCLE; (d) VGEB.

which means it can well reduce the probability that some nodes deplete energy ahead of time to affect the lifetime of the network. Hence, from Fig.3 (e), we can observe that the lifetime of network topology generated by TC-GSC algorithm is greater than that of the other algorithms.

C. Performance Versus Time

In TC-GSC, the topology would be reconstructed when the the active node's residual energy becomes uneven or the active node's working time exceeds the threshold. In this experiment, 200 nodes were randomly deployed in the area. From Table II and Table III, we know that the average transmitting power and node degree of TC-GSC increases over time. Besides, it is observed from Table II that the values of transmitting power of TC-GSC are lower than that of TCLE and VGEB but slightly higher than that of DIA. For example, when the number of nodes is 200, the average transmitting power of TC-GSC is 0.0536w, shorter than those of TCLE (0.0542w) and VGEB (0.0558w). From Table III, the node degree of TC-GSC is lower than those of TCLE and DIA, and the node degree curve of VGEB fluctuates sharply and the overall trend is greater than that of TC-GSC. These phenomena indicate that TC-GSC has obvious advantages in energy-saving. As shown in Table IV, the average hop number of the shortest path of TC-GSC is always smaller than those of other algorithms. We also know that the topology generated by TC-GSC have an apparent improvement in routing compared with those of other algorithms because it has the minimum hop number to transmit packets, which can reserve energy to prolong the network lifetime.

D. Residual Energy

As time passes, some nodes' energy may dissipate rapidly because of long time working or heavy relay tasks, which will make the residual energy of nodes gradually unbalanced. The residual energy of nodes with relatively centralized distribution can reflect the energy balance of network topology. Here, to evaluate the network topology's energy balance performance, we recorded the residual energy of the network nodes under four algorithms at $\mathrm{TC}(t) = 1 \times 10^2 r$. Fig.4 (a) shows that the residual energy distribution of TC-GSC is relative concentration, which indicates that TC-GSC can well schedule the network to maintain energy balance, and prevent individual nodes from dissipating quickly. As shown in Fig.4 (b) to Fig.4 (d), some nodes with residual energy distribution are too scattered, which may shorten the network lifetime. Although TCLE and VGEB consider the factor of energy, neither of them has a node scheduling mechanism, which leads to an unsatisfactory energy balance result.

The simulation results demonstrate that TC-GSC has obvious advantages over the existing algorithms in five network performance parameters; thus TC-GSC can effectively prolong the lifetime of IoT. Also, from Table II to Table IV, we know that TC-GSC excels in energy-saving and routing. The last experiment shows that the residual energy of TC-GSC is the most concentrated, which reflects the superiority of the TC-GSC in energy balance.

VI. Conclusion

We provided an effective method (TC-GSC) to maintain the energy balance. TC-GSC is to satisfy both goals of saving energy by reducing redundant data gathering and balancing the energy dissipation among the whole sensor network using game theory. Most existing works can only achieve one goal. The energy-saving strategy of TC-GSC is to partition each monitoring area into several correlation regions and to select one active node to report the data for each correlation region. However, this energy saving strategy based on spatial correlation analysis may incur unbalanced energy consumption due to some selfish sensor nodes. Therefore, we adopt game theory to optimize TC for achieving even energy consumption. Based on game theory, each node computes its transmitting power level and generates a connected topology. When the topology's energy consumption becomes unbalanced, the nodes will be dynamically re-selected and the topology will be reconstructed. The extensive simulation results demonstrate that TC-GSC can effectively improve the energy-balance of nodes and significantly reduce the energy waste, thus extending the lifetime of networks.

References

[1] S. Deepa, P. Haritha, S. Haridha, M. Harini, and V. K. Kiran, "Energy conservative data transmission using Z-Mac technique in wireless sensor network for environmental monitoring," in *Proc. IEEE Technol. Innov. ICT Agricult. Rural Develop. (TIAR)*, Chennai, India, Jul. 2016, pp. 194–199.

[2] E. Kanagaraj, L. M. Kamarudin, A. Zakaria, R. Gunasagaran, and A. Y. M. Shakaff, "Cloud-based remote environmental monitoring system with distributed WSN weather stations," in *Proc. IEEE Sensors*, Nov. 2015, pp. 1–4.

[3] J. Wang, I. S. Ahn, Y. Lu, and G. Staskevich, "A new distributed algorithm for environmental monitoring by wireless sensor networks with limited communication," in *Proc. IEEE Sensors*, Oct. 2016, pp. 1–3.

[4] Z. Xie, G. Huang, R. Zarei, J. He, Y. Zhang, and H. Ye, "Wireless sensor networks for heritage object deformation detection and tracking algorithm," *Sensors*, vol. 14, no. 11, pp. 20562–20588, Oct. 2014.

[5] X. Yang, W.-A. Zhang, L. Yu, and K. Xing, "Multi-rate distributed fusion estimation for sensor network-based target tracking," *IEEE Sensors J.*, vol. 16, no. 5, pp. 1233–1242, Mar. 2016.

[6] T. Azzabi, H. Farhat, and N. Sahli, "A survey on wireless sensor networks security issues and military specificities," in *Proc. Int. Conf. Adv. Syst. Electric Technol. (IC_ASET)*, Hammamet, Tunisia, Jan. 2017, pp. 66–72.

[7] R. Lara, D. Benitez, A. Caamano, M. Zennaro, and J. L. Rojo-Alvarez, "On real-time performance evaluation of volcano-monitoring systems with wireless sensor networks," *IEEE Sensors J.*, vol. 15, no. 6, pp. 3514–3523, Jun. 2015.

[8] R. S. Komali, A. B. MacKenzie, and R. P. Gilles, "Effect of selfish node behavior on efficient topology design," *IEEE Trans. Mobile Comput.*, vol. 7, no. 9, pp. 1057–1070, Sep. 2008.

[9] X. Lu, I. H. Kim, A. Xhafa, J. Zhou, and K. Tsai, "Reaching 10-years of battery life for industrial IoT wireless sensor networks," in *Proc. Symp. VLSI Circuits*, Jun. 2017, pp. C66–C67.

[10] L. Rodrigues, E. Leao, C. Montez, R. Moraes, P. Portugal, and F. Vasques, "An advanced battery model for WSN simulation in environments with temperature variations," *IEEE Sensors J.*, vol. 18, no. 19, pp. 8179–8191, Oct. 2018.

[11] P. Cheng, Y. Qi, K. Xin, J. Chen, and L. Xie, "Energy-efficient data forwarding for state estimation in multi-hop wireless sensor networks," *IEEE Trans. Autom. Control*, vol. 61, no. 5, pp. 1322–1327, May 2016.

[12] M. Javadi, H. Mostafaei, M. U. Chowdhurry, and J. H. Abawajy, "Learning automaton based topology control protocol for extending wireless sensor networks lifetime," *J. Netw. Comput. Appl.*, vol. 122, pp. 128–136, Nov. 2018.

[13] S. Kassan, J. Gaber, and P. Lorenz, "Game theory based distributed clustering approach to maximize wireless sensors network lifetime," *J. Netw. Comput. Appl.*, vol. 123, pp. 80–88, Dec. 2018.

[14] M. Vögler, J. Michael Schleicher, C. Inzinger, and S. Dustdar, "Optimizing elastic IoT application deployments," *IEEE Trans. Services Comput.*, vol. 11, no. 5, pp. 879–892, Oct. 2018.

[15] J. Haigh, "Game theory and evolution," *Adv. Appl. Probab.*, vol. 7, no. 1, pp. 8–11, 1975.

[16] D. Wolter Ferreira Touma and L. Lebensztajn, "Optimizing transcutaneous energy transmitter using game theory," *IEEE Trans. Magn.*, vol. 52, no. 3, pp. 1–4, Mar. 2016.

[17] A. Zappone, S. Buzzi, and E. Jorswieck, "Energy-efficient power control and receiver design in relay-assisted DS/CDMA wireless networks via game theory," *IEEE Commun. Lett.*, vol. 15, no. 7, pp. 701–703, Jul. 2011.

[18] S. Sasirekha and S. Swamynathan, "Cluster-chain mobile agent routing algorithm for efficient data aggregation in wireless sensor network," *J. Commun. Netw.*, vol. 19, no. 4, pp. 392–401, Aug. 2017.

[19] B. Kang, P. K. H. Nguyen, V. Zalyubovskiy, and H. Choo, "A distributed delay-efficient data aggregation scheduling for duty-cycled WSNs," *IEEE Sensors J.*, vol. 17, no. 11, pp. 3422–3437, Jun. 2017.

[20] P. Santi, "Topology control in wireless ad hoc and sensor networks," *ACM Comput. Surv.*, vol. 37, no. 2, pp. 164–194, Jun. 2005.

[21] A. A. Aziz, Y. A. Sekercioglu, P. Fitzpatrick, and M. Ivanovich, "A survey on distributed topology control techniques for extending the lifetime of battery powered wireless sensor networks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 121–144, 1st Quart., 2013.

[22] H. Üster and H. Lin, "Integrated topology control and routing in wireless sensor networks for prolonged network lifetime," *Ad Hoc Netw.*, vol. 9, no. 5, pp. 835–851, Jul. 2011.

[23] Y. Liu, Q. Zhang, and L. Ni, "Opportunity-based topology control in wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 21, no. 3, pp. 405–416, Mar. 2010.

[24] A. Cuzzocrea, A. Papadimitriou, D. Katsaros, and Y. Manolopoulos, "Edge betweenness centrality: A novel algorithm for QoS-based topology control over wireless sensor networks," *J. Netw. Comput. Appl.*, vol. 35, no. 4, pp. 1210–1217, Jul. 2012.

[25] S. Lin *et al.*, "ATPC: Adaptive transmission power control for wireless sensor networks," *ACM Trans. Sensor Netw.*, vol. 12, no. 1, pp. 1–31, 2016.

[26] H. Zhao and L. Guo, "Energy saving of wireless sensor network based on topology control algorithm," *IEEE Access*, vol. 7, pp. 85525–85535, 2019.

[27] Y. Chang, X. Yuan, B. Li, D. Niyato, and N. Al-Dhahir, "A joint unsupervised learning and genetic algorithm approach for topology control in energy-efficient ultra-dense wireless sensor networks," *IEEE Commun. Lett.*, vol. 22, no. 11, pp. 2370–2373, Nov. 2018.

[28] X. Chu and H. Sethu, "An energy balanced dynamic topology control algorithm for improved network lifetime," in *Proc. IEEE 10th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Larnaca, Cyprus, Oct. 2014, pp. 556–561.

[29] X. Liu, "A novel transmission range adjustment strategy for energy hole avoiding in wireless sensor networks," *J. Netw. Comput. Appl.*, vol. 67, pp. 43–52, May 2016.

[30] D. Shang, B. Zhang, Z. Yao, and C. Li, "An energy efficient localized topology control algorithm for wireless multihop networks," *J. Commun. Netw.*, vol. 16, no. 4, pp. 371–377, Aug. 2014.

[31] Y. Tian, M. Sheng, J. Li, and Y. Zhang, "Energy-aware self-adjusted topology control algorithm for heterogeneous wireless ad hoc networks," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Honolulu, HI, USA, Nov. 2009, pp. 1–6.

[32] H.-Y. Shi, W.-L. Wang, N.-M. Kwok, and S.-Y. Chen, "Game theory for wireless sensor networks: A survey," *Sensors*, vol. 12, no. 7, pp. 9055–9097, 2012.

[33] S. Eidenbenz, V. S. Anil Kumar, and S. Zust, "Equilibria in topology control games for ad hoc networks," *Mobile Netw. Appl.*, vol. 11, no. 2, pp. 143–159, Apr. 2006.
[34] R. S. Komali and A. B. MacKenzie, "Distributed topology control in ad-hoc networks: A game theoretic perspective," in *Proc. 3rd IEEE Consum. Commun. Netw. Conf. (CCNC)*, Las Vegas, NV, USA, vol. 1, 2006, pp. 563–568.
[35] Q. Tan *et al.*, "Energy harvesting aware topology control with power adaptation in wireless sensor networks," *Ad Hoc Netw.*, vol. 27, pp. 44–56, Apr. 2015.
[36] A. Nahir, A. Orda, and A. Freund, "Topology design of communication networks: A game-theoretic perspective," *IEEE/ACM Trans. Netw.*, vol. 22, no. 2, pp. 405–414, Apr. 2014.
[37] X.-C. Hao, Y.-X. Zhang, N. Jia, and B. Liu, "Virtual game-based energy balanced topology control algorithm for wireless sensor networks," *Wireless Pers. Commun.*, vol. 69, no. 4, pp. 1289–1308, Apr. 2013.
[38] M. Xu, Q. Yang, and K. S. Kwak, "Distributed topology control with lifetime extension based on non-cooperative game for wireless sensor networks," *IEEE Sensors J.*, vol. 16, no. 9, pp. 3332–3342, May 2016.
[39] X. Hao, L. Wang, N. Yao, D. Geng, and B. Chen, "Topology control game algorithm based on Markov lifetime prediction model for wireless sensor network," *Ad Hoc Netw.*, vol. 78, pp. 13–23, Sep. 2018.
[40] Y. Du, J. Gong, Z. Wang, and N. Xu, "A distributed energy-balanced topology control algorithm based on a noncooperative game for wireless sensor networks," *Sensors*, vol. 18, no. 12, p. 4454, Dec. 2018.
[41] I. Chatzigiannakis, T. Dimitriou, S. Nikoletseas, and P. Spirakis, "A probabilistic algorithm for efficient and robust data propagation in wireless sensor networks," *Ad Hoc Netw.*, vol. 4, no. 5, pp. 621–635, Sep. 2006.
[42] I. Chatzigiannakis, S. Nikoletseas, and P. Spirakis, "Efficient and robust protocols for local detection and propagation in smart dust networks," *Mobile Netw. Appl.*, vol. 10, nos. 1–2, pp. 133–149, Feb. 2005.
[43] C. Chen, T. Qiu, J. Hu, Z. Ren, Y. Zhou, and A. K. Sangaiah, "A congestion avoidance game for information exchange on intersections in heterogeneous vehicular networks," *J. Netw. Comput. Appl.*, vol. 85, pp. 116–126, May 2017.
[44] C. Efthymiou, S. Nikoletseas, and J. Rolim, "Energy balanced data propagation in wireless sensor networks," *Wireless Netw.*, vol. 12, no. 6, pp. 691–707, Dec. 2006.
[45] T. Qiu, R. Qiao, and D. O. Wu, "EABS: An event-aware backpressure scheduling scheme for emergency Internet of Things," *IEEE Trans. Mobile Comput.*, vol. 17, no. 1, pp. 72–84, Jan. 2018.
[46] L. A. Villas, A. Boukerche, H. A. B. F. de Oliveira, R. B. de Araujo, and A. A. F. Loureiro, "A spatial correlation aware algorithm to perform efficient data collection in wireless sensor networks," *Ad Hoc Netw.*, vol. 12, pp. 69–85, Jan. 2014.
[47] D. Monderer and L. S. Shapley, "Potential games," *Games Econ. Behavior*, vol. 14, no. 1, pp. 124–143, 1996.
[48] R. C. Luo, L. Chao Tu, and O. Chen, "An efficient dynamic power management policy on sensor network," in *Proc. 19th Int. Conf. Adv. Inf. Netw. Appl. (AINA papers)*, vol. 1, Taipei, Taiwan, 2005, pp. 341–344.
[49] M. Abbasi and N. Fisal, "Noncooperative game-based energy welfare topology control for wireless sensor networks," *IEEE Sensors J.*, vol. 15, no. 4, pp. 2344–2355, Apr. 2015.
[50] N. Li, J. C. Hou, and L. Sha, "Design and analysis of an MST-based topology control algorithm," *IEEE Trans. Wireless Commun.*, vol. 4, no. 3, pp. 1195–1206, May 2005.
[51] N. Meghanathan, "An algorithm to determine energy-aware maximal leaf nodes data gathering tree for wireless sensor networks," *Comput. Sci.*, vol. 15, no. 2, pp. 96–107, 2014.

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