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# An Optimized Clustering Communication Protocol Based on Intelligent Computing in Information-Centric Internet of Things

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**ABSTRACT** A narrow bandwidth may lead to a large amount of redundant data, which further causes the interruptions of the communication network. In order to address this problem, an optimized clustering communication protocol based on intelligent computing (CCP-IC) is proposed in this paper. First, we adopt the intelligent algorithm to perform the optimization of the clustering in the sensor network. The adaptation function and the heuristic function are introduced to make a targeted choice on the cluster head for the next hop of the nodes in the network. Second, the controllable threshold parameter and variation coefficient are employed to optimize the shortest path chosen by the network routing. Therefore, the node energy consumption is lowered when the minimum network delay is guaranteed and the transmission efficiency is improved. Finally, it is verified via the simulation results and compared with other algorithms; the proposed protocol reduces the network energy consumption by 15.3% and prolongs the network lifetime by 18.72%, which proves the validity and effectiveness of the proposed protocol.

**INDEX TERMS** Internet of Things, clustering communication protocol, intelligent computing, network lifetime.

## I. INTRODUCTION

Internets of Things (IoT) underlying system are organized by a large number of low-cost and small-scale sensor nodes in a self-organized method. The main task of IoT is to monitor the related objects in the network coverage area and transmit the monitoring results from the Sink to the observer. IoT is widely applied to a variety of engineering fields such as military and national defense, anti-terrorism, national security, emergency rescuing, space exploration, medical health, intelligent agriculture, and the construction of smart cities [1]–[4]. The importance of IoT has drawn much attention from different fields.

In order to cope with the problems of failed nodes and data sensing inaccuracy caused by the environment, sensor nodes of the sensor network are usually densely deployed in the monitoring area [5], [6]. However, this also leads to the heavy information redundancy within the network. If the Sink directly collects all the original data, a large amount of precious energy is wasted during the transmission of the redundant data [7]–[9]. To address this problem, the data aggregation technique employs different methods to process the sensing data and further reduces the transmission of redundant data within the network. Therefore, the data aggregation technique is a very important technique to realize the efficient data collection in IoT [10]. Data collection is the major task of IoT and lays the foundation for all the applications of IoT. The data collection of IoT can be categorized into three types: data-driven type, search-driven type and event-driven type. For the data-driven data collection, the sensor nodes periodically sense the environment and

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transmit the sensing data to the Sink at a fixed data rate which is determined by a pre-scheduling strategy [11], [12]. This type of data collection is also termed the periodical data collection and it is applicable to the applications where the global monitoring is required, i.e., all the nodes in the network transmits sensing data. For the search-driven data collection, the Sink sends the data collection request according to the requirement of the users. Only when the sensor nodes satisfy the requests, will they transmit their sensing data. For the event-driven data collection, an arbitrary node remains silent until the target event happens and only when the node detects the occurrence of the event, will it transmits the event-related data to the Sink. These nodes are usually partial nodes and the randomness of events causes the random distribution of these nodes.

Data aggregation refers to the operation that the sensor node performs aggregation on its sensing data or multiple received data. The aim of data aggregation is reducing the redundancy, enhancing the data accuracy, improving the data collecting efficiency and saving energy. The data aggregation can be divided into two types, complete data aggregation and partial data aggregation. The complete data aggregation means that the size of the transmitted aggregation data packet is fixed no matter how much data is received by the sensor node. The partial data aggregation equals to that the amount of the aggregation data is smaller than the total amount of the original data. If the correlation of the original data is stronger and the data aggregation efficiency is higher, the amount of the aggregation data will be smaller. To realize the data aggregation within the wireless sensor network, the original data must be aggregated in time and space during the transmission. Therefore, we need to design an appropriate routing scheme so that the data transmission could optimize the spatial and temporal aggregation. Then higher data aggregation efficiency can be obtained as the amount of transmitted data within the network is reduced. The data aggregation-based routing technology in wireless IoT can be divided into three types: structured, unstructured, and semi-structured. The structured routing for data aggregation can be further divided into chain structure, tree structure, and cluster structure. The unstructured routing for data aggregation is a network routing without maintaining any specific network structure, where the proper neighbor nodes are immediately chosen to transmit the message via the appropriate information exchange. The semi-structured routing is a hybrid of the other two types.

## II. RELATED WORK

Chain-structure routing algorithm for data aggregation has attracted much research interest and many efforts have been made in this area. A typical example is paper [13].And in this work, according to the location of the nodes; a greedy algorithm was employed to generate a chain on which the distance between the neighbor nodes is the shortest. The responsibility of chain head is taken by every node in turn and the chain head was responsible for transmitting the aggregation data to the Sink. Paper [14] organized the nodes in a two-level chain structure, which is composed of multiple low-level chains with fixed length and one high-level chain composed of chain head nodes of the low-level chains. The data was transmitted and aggregated from the low-level chains to the high-level chains and finally received by the Sink. Paper [15] introduced the distance threshold to avoid the long chains and elect the nodes with more remaining energy and closer to the Sink as the chain heads. Therefore, the node energy consumption is balanced. Paper [16] partitioned the network region into many rings, sharing the same center while the nodes within each ring were generated according to the PEGASIS algorithm. The data was first transmitted to the chain head and then transmitted to the Sink along the chain heads from outside to inside. Paper [17] horizontally partitioned the monitoring area into many square sub-areas with the same size. The routing chain was formed via the greedy algorithm for the nodes within the same sub-area. Similar to the ECR, Paper [18] first partitioned the network into many square sub-areas. But this algorithm partitioned the network area vertically and the uniform gradient algorithm was employed within each sub-area to form the routing chain, instead of the greedy algorithm. The Beam-Star technique was employed in Paper [19] to partition the entire area into many sector areas. Then, a method similar to PEGASIS was employed to establish the short chains and all the chain heads composed the routing chain connected to the Sink. Paper [20], [21] were proposed to calculate the transmission cost based on the optimal power. When a minimum-cost tree is established, the distributed depth-first-search is employed to construct a routing chain starting from the Sink. Paper [22] first employed Buttenfield's Strip Tree Geometry algorithm to obtain a hierarchy tree. Then, based on this tree, the in-order-traversal search was utilized to obtain a routing chain containing all the nodes. Papers [23] proposed a minimum spanning tree (MST)-based construction algorithm for the routing chain. An undirected MST was first constructed, then the node closest to the network center was chosen as the root and the breadth-first-search was employed to obtain a directed MST. Finally, the pre-order traversal, in-order traversal, and post-order traversal were employed to obtain a routing chain containing all the nodes in the network. Paper [24] partitioned the whole area by grids. The node with the most remaining energy in each unit grid was elected as the head and all the heads formed a routing chain where the head with the most remaining energy served as the chain head. Paper [25] employed the locations of the one-hop neighbors or the distance information to construct the local MST and related neighbor graph. Then three different schemes were used to choose the parent nodes and further construct the data aggregation tree. For the wireless sensor network with different initial node energy, paper [26] investigated on the problem of finding a data aggregation tree among the minimum-distance trees to maximize the network lifetime. This problem was equivalent to finding a minimum distance tree with a minimum load and it was solved by the transformation into the generalized semi-matching sub-problem. A depth-first-search and breadth-first-search based distributed algorithm was further proposed for the construction of the minimum-distance trees. Paper [27] put forward a double-tree routing scheme which employed the reverse chain, MST and SPT to construct two routing trees. For wireless IoT with multiple mobile Sinks, paper [28] designed a branch-defining algorithm and an analog backfire algorithm to construct the minimum Wiener index spanning tree and further obtain better energy efficiency and lower data delay. The Sink was required to choose the root node according to the energy and data aggregation type while the other nodes employed their location information and the neighbors' information to choose the parent node. Finally, a routing tree with balanced energy consumption was constructed in a distributed manner. For the probability network model, paper [29] first used the linear slack and random round-off technology to construct a maximum independent set with balanced load. Based on that, a connected maximum independent set was obtained. Then the assignment of the parent nodes with balanced load was performed and finally a direction was assigned to each chain so as to obtain a data aggregation tree. Paper [30] constructed the tree level by level from the Sink and guaranteed that the number of child nodes for all the nodes remained the same. Then a routing tree was established with globally balanced load. Based on an established routing tree with shortest path, the load-balance-based tree structure adaptation factor was performed iteratively from bottom to top. Iteration involved the grandparent nodes, parent nodes and child nodes. Paper [31] considered the transmission cost and the data aggregation cost. Based on the routing tree constructed by the MFST algorithm, a data aggregation routing tree was obtained with higher energy efficiency. Meanwhile, the benefit brought by the data aggregation was evaluated so that the data aggregation behavior of the nodes could be adjusted adaptively. Paper [32] designed a centralized algorithm with polynomial time complexity and a distributed algorithm based on local information to customize the optimal transmission strategy for a tree and assign related slots for each node to perform transmission, which could optimize the data aggregation. For duty-cycled wireless sensor network, papers [33] were based on the connected support set to construct the routing tree and proposed the centralized greedy aggregation scheduling (GAS) and partitioned-based distributed aggregation scheduling (PAS). Paper [34] divided the network time into rounds, and the cluster heads were chosen according to the round index and the formation of the cluster. The other nodes were added into the clusters where the cluster head has the strongest signal. Paper [35] calculated the hybrid cost of the nodes according to the remaining energy of the nodes and the other parameters, such as the node degree. Then the nodes with more energy and lower hybrid cost were periodically chosen as cluster heads. Paper [36] classified the member nodes according to their distances to the cluster head while the member nodes chose the neighbor nodes with the least child nodes in the previous class as their parent nodes. Finally, the data aggregation tree within the cluster was established with the cluster head as its root. Papers [37] were based on the node location, data similarity and node remaining energy and employed the analog backfire algorithm to establish the cluster structure. Then the auto-regression prediction model was employed to obtain the prediction data which determined the transmission of the data.

Based on the work in paper [15], paper [19] and paper [27], we propose an Optimized Clustering Communication Protocol Based on Intelligent Computing (CCP-IC), which is a distributed algorithm that could tolerate the overhead and achieve the distributed clustering of the nodes in the event domain and establishment of the network hop tree. The adaptive function and heuristic function are introduced with the help of intelligent algorithm, and as a result of which we can choose the location of the next-hop cluster head more accurately. By employing the controllable threshold and the variation coefficient, the shortest path chosen by the network routing is optimized, and then the node energy consumption is reduced while the network delay is minimized. The existence of long paths is curbed by the updating strategy of the global information element so that the node energy becomes balanced and the network resource allocation scheme is optimized. The proposed protocol can also effectively perform the data aggregation within the cluster to reduce the transmission of the redundant network data. Therefore the network routing structure is effectively maintained and the reliable data transmission is guaranteed.

## III. NETWORK MODELING AND ANALYSIS

### A. ASSUMPTIONS

From the perspective of maximizing the degree of data aggregation, the optimization problem of the network routing structure is equivalent to finding a Steiner tree connecting all the nodes in the event domain. It is shown via research that finding such a Steiner in a graph connecting the subsets is a NP-hard problem and we can only employ the heuristic methods to find an approximate solution [38], [39]. A variety of construction schemes close to the construction of the Steiner tree have been proposed for IoT. However, these schemes share the same problem of heavy control overhead. Actually, for the multi-hop sensor network with fixed nodes, if the complete data aggregation is not employed, then the load will be heavy for the node transmitting aggregation data and this node may suffer from early energy exhaustion. Therefore, it requires more energy to maintain the network. In addition, all the data within the network has to be transmitted to the Sink through the one-hop neighbors of the Sink and the lifetime of these one-hop neighbors determines the network lifetime. However, since they have the heaviest load, their early death caused by the energy exhaustion (hotspot problem) undermines the performance of the network.

For a better investigation on the clustering protocol for the data aggregation, we consider the following 6 assumptions:

(1) At the initialization period, all the nodes show the same isomorphic shape and they remain the round shape.

(2) The sensing radius is far smaller than the edge of the monitoring area, i.e., $R(s_i) << l$, and we neglect the boundary effect.

(3) All the sensor nodes in the network share the same priority and the location information can be acquired by the nodes through the positioning algorithm.

(4) An arbitrary sensor node is uniquely identified by an ID and all the nodes are synchronized in time.

(5) In the working period, the energy of the cluster head is higher than that of the other nodes.

(6) The communication among the sensor nodes is performed in a wireless method.

### B. BASIC DEFINITIONS

*Definition 1:* The undirected graph $G = (V, E)$ is used to describe the network topology, where $V \in R^2$ is the set of sensor nodes on a Euclidean plane. Each element $s_i$ represents a sensor node, and $E \in V^2$ is the set of edges while each edge $e = (s_i, s_j) \in E$, and $\{s_i, s_j\} \in V$. $R(s_i)$ is the transmission radius of the node $s_i$ while the Euclidean distance $d(s_i, s_j) \leq R(s_i)$.

*Definition 2:* In the graph $G = (V, E)$, if we find a subset $S \subseteq V$ with $S \neq \varphi$, then for $\forall s_i \in V - S$, $S$ is neighboring to at least one node in $V - S$. Then we define $S$ as the dominant set of graph $G$. The nodes in the dominant set are defined as the dominant nodes while the nodes not in the dominant set are defined as the dominated nodes.

*Definition 3:* That $H$ is the set of the cluster heads, which is called as the dominant set of the network, is assumed. The cluster head as $h_i$, $h_i \in H$, $H \subset V$ is denoted. It is defined that $h(s_i)$ as the cluster head of node $s_i$, $\forall s_j \in \{V - H\}$, $\exists h_i \in H$, which guarantees $h(s_j) = h_i$.

*Definition 4:* Define the Cluster Member (CM) set of $h_i$ as $M(h_i)$, $\cup_{\forall h_i \in H} M\,(h_i) = V - H$. For $S_j \in \{V - H\}$, if $d(s_j, h_i)$ is smaller than the distance from $s_j$ to the other cluster heads, then $s_j \in M(h_i)$.

*Definition 5:* Define $C(h_i) = \{h_i, M(h_i)\}$ as the set of nodes with cluster head $h_i$, denoted as $\cup_{\forall h_i \in H} C\,(h_i) = V$.

*Definition 6:* The load balance among all the cluster heads, i.e. $\{[(1/k) - \delta] \leq [C(hi)/n] \leq [(1/k) + \delta]\}$, where $\delta$ is the unbalance factor which depends on the realistic load capability. In order to balance the network load, set $\delta \to 0$.

*Definition 7:* Define $C$ as the data aggregation rate, i.e., the original data amount is n while the data amount after data aggregation is $m$. Then $C = m/n$ and a smaller $C$ indicates a higher data aggregation rate. The complete aggregation indicates $m = 1$ and $C = 1/n$.

### C. NETWORK MODEL

In the event-driven IoT, the distributed clustering, based on the nodes in the event domain and the aggregation on the data within the cluster, is one effective method to reduce the data transmission amount. The degree of data aggregation is related to the correlation among data. A higher correlation means less data after aggregation. Merely from the perspective of data aggregation, the data aggregation should happen as soon as possible regardless of the data correlation. If the data aggregation is the complete aggregation, then constructing an energy efficient routing structure is equivalent to constructing an approximate Steiner tree based on the nodes in the event domain. If the data aggregation is incomplete, the approximate Steiner tree -based routing structure could still make sure the data aggregations happen as early as possible. But this can lead to the early death due to the heavy load on partial nodes, which increase the energy consumption to maintain the network and wastes the energy saved by the data aggregation.

The main purpose of clustering is to realize the energy balance among nodes, enhance the error tolerance of the network, increase the connectivity and minimize the cluster number, which could finally prolong the network lifetime. According to the requirement of the system, the task of clustering algorithms is to employ a certain rule to partition the network into multiple clusters which can mutually communicate and cover all the nodes, and meanwhile the cluster structure should be updated when the network changes, so that the normal functioning of the network can be guaranteed. The basic idea is to divide the geologically neighboring nodes in the network into the adjacent areas so the small-range manageable logic structure can be formed within the network. The cluster structure in the IoT is illustrated in Fig. 1, where each divided area is defined as a cluster and each cluster is normally governed by a cluster head and composed of several cluster members. The cluster heads of lower-level networks are the cluster members of higher-level network while the cluster heads in the highest level are in charge of the communication with the gateway. Under the clustered topology management mechanism, nodes in the network can be divided into cluster head nodes and cluster member nodes. The cluster heads are elected according to a certain clustering algorithm or rules, and they take charge

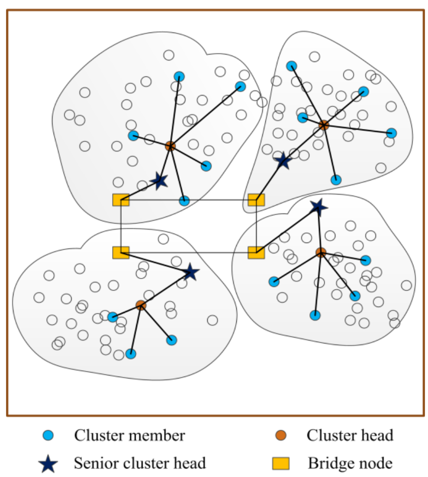


**FIGURE 1.** Clustering structure in IoT.

of managing the cluster members and coordinating the work of the cluster members. The cluster heads also perform data collection within the cluster and data aggregation as well as data relay between clusters. Apart from the cluster heads, all the other nodes are termed cluster members while the cluster nodes simultaneously belonging to two or more clusters are termed gateway nodes. Nodes in different clusters but within each other's communication range are termed network bridge nodes.

The CCP-IC problem is to find the optimal path in the clustered network which starts from the source node and connects all the other member nodes in the current cluster and finally reaches the cluster head. This path should be the shortest one, satisfying all the constraints.

### D. BASIC DEFINITIONS

According to the assumptions above, at the initial time of the network, all the nodes share the same energy and priority. Therefore, the information elements on each path are the same. Assuming that $\tau_{ij} = C$, where $C$ is a constant, and the probability that $k$ is transitioned on the path is:

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t) \cdot \eta_{ij}^{\beta}(t)}{\sum\limits_{s \in Set1} \tau_{is}^{\alpha}(t) \cdot \eta_{is}^{\beta}(t)} \\ 0 \end{cases} \tag{1}$$

where Set1 $= \{1,2,3\ldots n\}$-Set2, indicating the next available target node to be chosen by the current node $k$. Set2 is the set of nodes currently chosen. Set1 and Set2 are dynamically adjusted with time. When a network has been working for 1 period or $N$ periods, the number of information elements on the path is going to gradually reduce to 0 and the consecutively controllable parameter $\rho$ is also going to decrease where 1-$\rho$ indicates the decreasing degree of information. When one data transmission is accomplished from the source node to the Sink node, the amount of information on different paths should be adjusted as follows:

$$\tau_{ij}(t+n) = \rho \tau_{ij}(t) + (1-\rho)\Delta\tau_{ij} \tag{2}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{3}$$

where $\Delta\tau_{ij}^{k}$ represents the amount of information left by the $k$-th node on path $(i,j)$, $\Delta\tau_{ij}$ is the increased amount of information on path $(i,j)$ in this iteration.

Assuming that $R_+$ is the set of all the positive integers while $R^+$ is the set of all the non-negative integers, for an arbitrary link $e \in E$, we define four metrics: delay function Delay$(e) : E \rightarrow R_+$, where the network delay refers to the average time required to transmit a data packet in the network; the delay jitter function Delay-jit$(e) : E \rightarrow R^+$, where the network jitter refers to the variation of transmission time for a data packet. These two functions are two important factors which might undermine the network transmission quality. The bandwidth function Bandwidth$(e) : E \rightarrow R_+$, where the network bandwidth is the decisive factor to reduce the end-to-end delay for the network; the cost function Cost$(e) : E \rightarrow R_+$, which reflects the energy consumption from the network source node to the destination node. We also define four metrics functions for an arbitrary network node $n \in V$, i.e., the delay function: Delay$(n) : E \rightarrow R_+$, the delay jitter function Delay-jit$(e) : E \rightarrow R^+$, the cost function cost$(n) : E \rightarrow R_+$ and the packet loss function: Loss-packet$(n) : V \rightarrow R^+$. During the transmission, the data packets might be lost or damaged and the data would be highly incomplete if the packet loss rate is too high. For a given source node $s \in V$, a set of destination nodes $M$, the following equations hold for the multi-cast tree $T(s, M)$, composed of $s$ and $M$.

$$\text{delay}(P_T(s,u)) = \sum_{e \in P_t(s,u)} \text{delay}(e) + \sum_{n \in P_T(s,u)} \text{delay}(n) \tag{4}$$

$$\text{cost}(T(s,M)) = \sum_{e \in P_T(s,u)} \text{cost}(e) + \sum_{n \in P_T(s,u)} \text{cost}(n) \tag{5}$$

$$\text{bandwidth}(P_T(s,u)) = \min\{\text{bandwidth}(e), n \in P_T(s,u)\} \tag{6}$$

$$\text{delay-jit}(P_T(s,u)) = \sum_{e \in P_t(s,u)} \text{delay-jit}(e) + \sum_{n \in P_T(s,u)} \text{delay-jit}(n) \tag{7}$$

$$\text{loss-packet}(P_t(s,u)) = 1 - \prod_{n \in P_T(s,u)} (1 - \text{loss-packet}(n)) \tag{8}$$

where $P_T(s, u)$ is the routing path from source node $s$ in the upper layer of $T(s, M)$ to the destination $u$.

## IV. ANALYSIS AND REALIZATION OF CCP-IC ALGORITHM

### A. FORMATION OF CLUSTERS

The formation of clusters is divided into two phases. The first one is the declaration phase of cluster heads while the second one is the formation of clusters. In the first phase, at the initialization time of the network, the number of all the sensor nodes in the monitoring area is calculated and the cluster heads are randomly chosen. Then one request frame is broadcast in a flooding schedule from these cluster heads to all the data collecting nodes. The request frame includes the ID information and location information of the node, which claims the identity as cluster heads. In the node, which is claimed as the cluster head, there is a structured chain used to record the nodes in the related topology of this node, such as the ID information, location information, remaining energy, sensing ability and distance information. The data collecting nodes receive the claim of the cluster head and store it in its topology structure chain. In the next period, the nodes within the cluster compete for the position of cluster head according to the weights and variation range of parameters. The second period is the formation of the clusters when the other nodes calculate the distance to the cluster head after receiving the claim of the cluster head. The distance calculated is then compared with the distance stored in the topology structure chain. If the calculated distance is shorter than the distance in the topology structure chain, this node replaces the original cluster head with itself. At the same time, the node receives the request frame, and the number of received frames is also recorded. When the number of received frames is equal to the number of cluster heads in the network, the node sends a confirmation frame to the cluster heads, which includes its ID and location information, etc. and stops receiving more request frames. After receiving the confirmation frame, the cluster head lists the corresponding node as its cluster member node and store the location and ID information in the member list. After several periods, the cluster head stops the broadcasting while each sensor node is added into one cluster. The cluster head could directly perform communication with a large transmission distance to all the nodes within the cluster. But if the cluster head directly communicates with all the nodes, the burden can be heavy and the difference for the member nodes and the cluster head may therefore exist, which further causes unbalanced links. Therefore, in the formation of clusters, power control on the cluster heads can help eliminate unbalanced links, which achieves the bi-directional connectivity for the network.

*Theorem 1:* The deletion in the graph of asymmetric chains will not affect the connectivity of the sub-graph $G'$.

*Proof:* Since $G'$ is a connected sub-graph of $G, \forall s_j \in C(h_i)$, $h_i \rightarrow s_j$, i.e., $h_i$ and $s_j$ are mutually connected. Assuming that $d(h_i, s_j) < R(h_i)$ and $d(h_i, s_j) > R(s_j)$, then there is a directed path $l = s_j \rightarrow s_l \rightarrow \ldots \rightarrow s_k \rightarrow h_i$ between $s_j$ and $h_i$. Due to the homogeneity among different nodes, there is $s_i \rightarrow s_j \Leftrightarrow s_j \rightarrow s_{i,}$, and thus $s_k \rightarrow s_l \rightarrow \ldots \rightarrow s_j$. Since $R(h_i) \geq R(s_k)$, $s_k \rightarrow h_i \Rightarrow h_i \rightarrow s_k$. Therefore, we can get $h_i \rightarrow s_k \rightarrow s_l \rightarrow \ldots \rightarrow s_j$. Even if the directed edge $(h_i, s_j)$ is deleted, the bi-directional connectivity between $h_i$ and $s_j$ is not affected. The proof is completed.

*Theorem 2:* At least one path exists where the probability $\Pr(\neg B_m)$ of the optimal path moving at $m$ nodes is no smaller than $1 - (1 - c^{m-1}p)S$, where $C = (1-\rho)^{\mathrm{L}}$ and $p = \gamma^L \prod_{(k,l)\in w^*} \tau_{kl}$.

*Proof:* When and only when assuming that the set of edges from the source node to the destination node is $(k, l)$ while the finite routing path is $u$, then:

$$\gamma = \min\left\{[\eta_{kl}(u)]^{\beta} \mid (k,l) \in w^*, u \in w^*\right\} > 0 \tag{9}$$

Since $\Delta\tau_{kl} \geq 0$ and $\rho > 0$, for the set of edges from the source nodes to the destination node, the value of $\tau_{kl}$ remains the same in period $m+1$ and $m$. If the constant $C > 0$:

$$\tau_{kl}(m+1) = (1-\rho)\,\tau_{kl}(m) + \rho\Delta\tau_{kl} \tag{10}$$

$$\Delta\tau_{kl} = \frac{1}{C}\sum_{s=1}^{S}\Delta\tau_{kl}^{(s)} \tag{11}$$

According to equations (10) and (11):

$$\tau_{kl}(m+1) \geq (1-\rho)\,\tau_{kl}(m) \tag{12}$$

Since the value of $\tau_{kl}$ remains the same in period $m+1$ and $m$, we can obtain equation (13) with the recursive algorithm.

$$\tau_{kl}(m) \geq (1-\rho)^{m-1}\,\tau_{kl}(1) \tag{13}$$

Without losing any generality, assuming that the expectation $\eta_{kl}(u)$ can be normalized with the $\Gamma = 1$ method, i.e., we perform the global optimization on the set of all the routing paths $(k, l)$. Then we can obtain that:

$$f(x) = \begin{cases} [\eta_{kl}(u)]^{\beta} \leq 1 \\ \sum \tau_{kl}(m) = 1 \end{cases} \tag{14}$$

$$\sum_{r\notin u,(k,r)\in A} \tau_{kr}(m)\,[\eta_{kr}(u)]^{\beta} \leq \sum_{r\notin u,(k,r)\in A} \tau_{kr}(m) \leq 1 \tag{15}$$

According to the transition probability in equation (1), we can obtain that when the node $r \notin u$, the following inequality holds:

$$p_{kl}(m,u) = \frac{\tau_{kl}(m)\,[\eta_{kl}(u)]^{\beta}}{\sum\limits_{r\notin u,(k,l)\in A} \tau_{kr}(m)\,[\eta_{kl}(u)]^{\beta}} \geq \tau_{kl}(m)\,[\eta_{kl}(u)]^{\beta} \tag{16}$$

According to equations (9), (13) and (16), we can further obtain that:

$$\begin{aligned} \Pr\left(E_m^{(s)}\right) &= \prod_{i=0}^{L-1} p_{v_i v_{i+1}}(m, (v_0, v_1 \cdots v_i)) \\ &\geq \gamma^L \prod_{i=0}^{L-1} (1-\rho)^{m-1}\,\tau_{v_i v_{i+1}}(1) = c^{m-1}p \end{aligned} \tag{17}$$

Since the nodes are mutually independent, we can employ the probability theory and obtain that:

$$\Pr(B_m) \leq \left(1 - c^{m-1}p\right)^S \tag{18}$$

$$\Pr(\neg B_m) \geq 1 - \left(1 - c^{m-1}p\right)^S \tag{19}$$

The proof is completed.

### B. ESTABLISHMENT AND MAINTENANCE OF THE ROUTING HOP TREE

The CCP-IC employs the clustered routing algorithm to obtain the routing in a centralized method. However, this algorithm requires the normal death of the nodes so that the mobile Sink can be informed of the routing update. If a node $v$ suffers from the unnatural death, like the damage caused by natural causes, the mobile Sink cannot update the routing on time. As a result, the node at the next hop cannot obtain the correct routing data. In order to address this problem, we adopt the following scheme: when the next-hop node of one node is dead, it chooses the node geologically closest to the Sink among all the neighbors as the next-hop node.

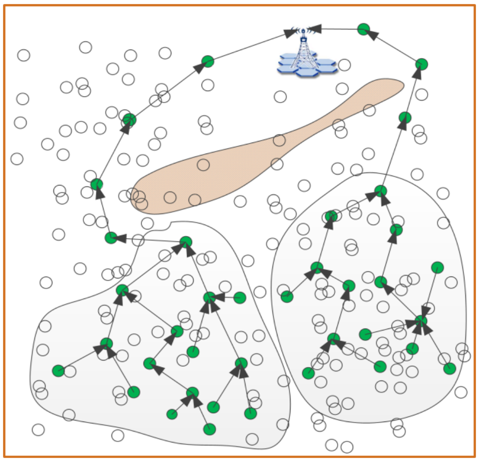

**FIGURE 2.** The clustered routing constructed by the CCP-IC under normal conditions.

But this scheme works poorly when there are obstacles in the monitoring area. The routing structure constructed by the CCP-IC algorithm is illustrated in Fig. 2 where there are no dead nodes and this scenario is the normal clustered routing status. In addition, inaccurate global information could lead to wrong and inefficient routing, obtained by the centralized routing construction algorithm. The CCP-IC employs a hop tree construction and maintenance method exhibiting better robustness. The hop tree in the network is established in a distributed method by the Hop Configuration Message (HCM) sent from the Sink in a flooding schedule. If a node $v$ is dead unnaturally, the next-hop node of $v$ is chosen with the least number of hops to the Sink and the highest remaining energy. It is not required to wait for the Sink to update the routing. The advantages for the hop tree establishment and maintenance method of the CCP-IC are shown in Fig. 3.

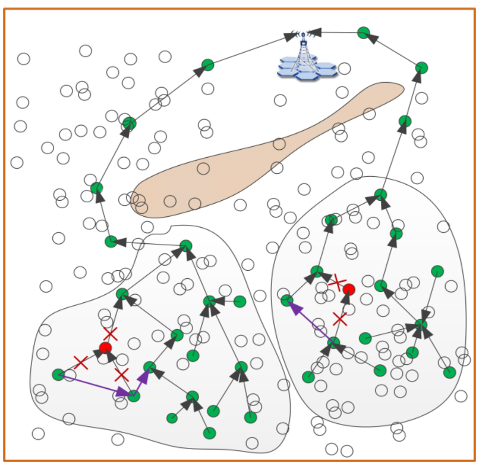

**FIGURE 3.** The clustered routing constructed by the CCP-IC under abnormal conditions.

The data transmission is divided into two major parts: the intra-cluster transmission and the inter-cluster transmission. The intra-cluster data is transmitted along the intra-cluster hop tree to the cluster head. All the non-leaf nodes can perform data aggregation while the cluster heads perform the deep aggregation on the data within the cluster, which greatly reduces the redundant data in the network. For the inter-cluster transmission, the aggregated data is transmitted to the Sink along the network hop tree. Since the aggregated data is transmitted, the data loss is huge once a block packet loss occurs [23]. Therefore, we adopt the message equivalence mechanism so as to guarantee the reliability of the data transmission.

With the running of the network, some nodes may be dead, requiring the routing maintenance. If a node is normally dead, it will inform the neighbors. Otherwise, the neighbors will detect its death via the periodical check. The nodes taking the dead node as the next-hop node will choose another next-hop node with the least hops and most remaining energy among all the neighbors. Additionally, at set intervals, the cluster head calculates its cluster information as the event information, which is included in the data message transmitted to the Sink. For the included event information, it will be ignored by the Sink if it is not recorded in the list. Otherwise, to facilitate the quasi-optimal location calculation, the cluster head updates the corresponding entry in the list for this event.

### C. SHIFTING ALGORITHM FOR THE CLUSTER HEADS

Since the cluster head is in charge of the intra-cluster management, the energy consumption is huge. If the cluster head is fixed, its energy will run out quickly. Therefore, the shifting for the cluster heads is necessary. During the shifting process, the cluster head should be chosen according to the data transmission round, the number of node hops and the remaining energy; so that the responsibility as cluster head is balanced and the energy consumption for cluster re-establishment can be saved. When the optimal candidate node does not have enough energy to finish the cluster re-establishment, the current cluster head will send a location information message to the Sink which urges the Sink to calculate the new quasi-optimal location and update the network routing. As a result, the data loss in the event field caused by the absence of cluster heads can be reduced as much as possible.

## V. SIMULATIONS

The CCP-IC is also compared with the following algorithms: a Distributed and Morphological Operation-based Data Collection Algorithm, DMOA [15] and the Multiple Target Tracking Algorithm and MTTA [27]. DMOA is an event-driven non-clustering algorithm in IoT while MTTA is event-based coverage control algorithm which adopts the dynamic clustering to achieve the tracking on the mobile target. Both algorithms employ the fixed Sink. However, the CCP-IC is a combination of clustering and controllable parameter. Through comparison, the advantages created by the clustering and controllable parameter can be illustrated. For a more convenient comparison, we employ the energy consumption model from paper [19]. The occurrence time, duration and location of the events in the monitoring area are assumed to be randomly distributed. The data aggregation is performed within the cluster for CCP-IC and MTTA and different data aggregation rates are considered.

### A. NETWORK LIFETIME

The network lifetime performances with different parameters are shown from Fig. 4 to Fig. 11. According to Fig. 4 and Fig. 5, when $\{\alpha = 0.1, \beta = 1.0, \rho = 0.1\}$, $\{\alpha = 0.3, \beta = 1.2, \rho = 0.2\}$ and $\{\alpha = 0.5, \beta = 1.5, \rho = 0.3\}$, $\{\alpha = 0.7, \beta = 1.8, \rho = 0.5\}$, the proposed algorithm remarkably outperforms the other two algorithms. With the increasing number of the sensor nodes, the network lifetime is also prolonged for all the three algorithms. Since the proposed CCP-IC algorithm adjusts the network lifetime through the dynamic configuration of the parameters, the initial period the proposed algorithm shows much longer network lifetime. When the number of sensor nodes is equal to 30, the network lifetime of the proposed algorithm could reach 188s, 231s, 230s, and 278s under different scenarios and it tends to be in a balanced state. By contrast, when the number of sensor nodes is equal to 30, the network lifetime is 102s, 161s, 135s, and 201s respectively for the DMOA and the MTTA. Therefore, the CCP-IC algorithm could prolong the network lifetime by 18.72% on average. Then main reason behind this is that with the controllable parameter, the data aggregation ability is enhanced for the proposed algorithm and the cluster-based message report mechanism reduces the number of control messages required to obtain the event information. Meanwhile, the intra-cluster data aggregation reduces the transmission of redundant data, which enables more neighbors to have the chance to become the one-hop neighbor of the Sink. Based on the number, location and average power of nodes in the event field, obtaining the quasi-optimal Sink location can reduce the data transmission distance and achieve a better energy balance. However, neither DMOA nor MTTA is capable of adjusting the parameter. Instead, the original tendency is remained. Therefore, with the increasing number of sensor nodes, the network lifetime of the proposed algorithm is longer than that of the other two algorithms. For the monitoring area with size $200 \times 200\text{m}^2$, $300 \times 300\text{m}^2$ and $400*400\text{m}^2$, similar results can be observed.

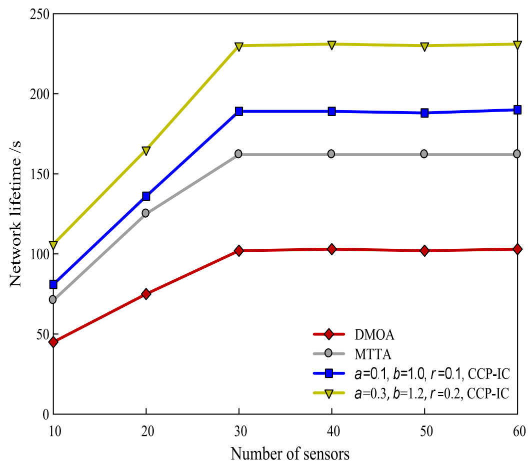


**FIGURE 4.** Network lifetime with $100 \times 100\text{m}^2$ monitoring area and different $\{\alpha, \beta, \rho\}$ parameters.

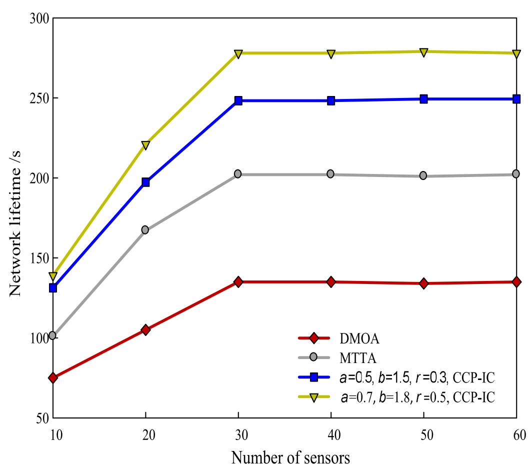


**FIGURE 5.** Network lifetime with $100 \times 100\text{m}^2$ monitoring area and different $\{\alpha, \beta, \rho\}$ parameters.

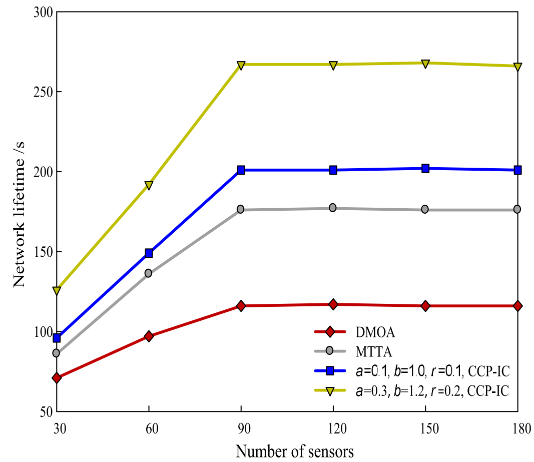


**FIGURE 6.** Network lifetime with $200 \times 200\text{m}^2$ monitoring area and different $\{\alpha, \beta, \rho\}$ parameters.

### B. NETWORK ENERGY

The network energy with different number of sensor nodes and $300*300\text{m}^2$ monitoring area is illustrated in Fig. 12 and Fig. 13. The controllable parameter in Fig. 12 is $\{\alpha = 0.1, \beta = 1.0, \rho = 0.1\}$, $\{\alpha = 0.3, \beta = 1.2, \rho = 0.2\}$ while that for Fig. 13 is $\{\alpha = 0.5, \beta = 1.5, \rho = 0.3\}$, $\{\alpha = 0.7, \beta = 1.8, \rho = 0.5\}$. Take Fig. 12 as an example; with the increasing number of sensor nodes, the network energy also increases. Within the same time duration, the proposed algorithm exhibits higher network energy than the other two algorithms. The increasing rate gets slower with the increase of sensor nodes for the DMOA algorithm. The main reason

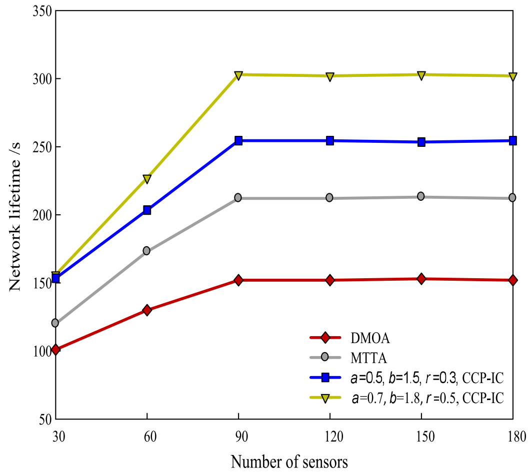


**FIGURE 7.** Network lifetime with 200 × 200m² monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

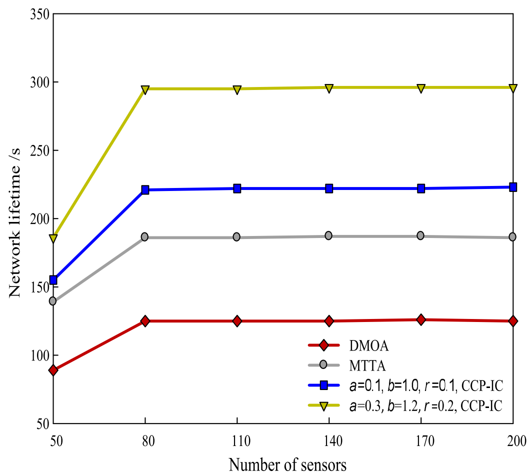


**FIGURE 8.** Network lifetime with 300 × 300m² monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

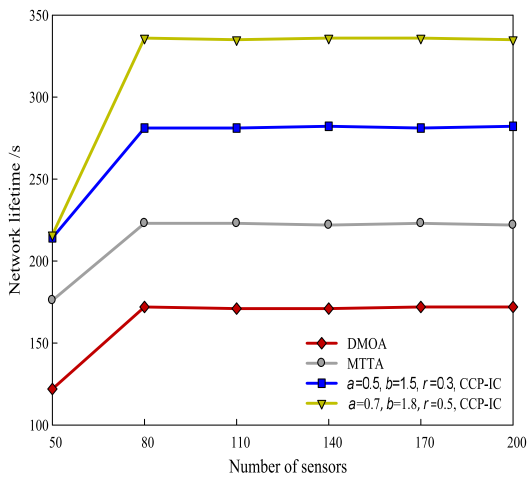


**FIGURE 9.** Network lifetime with 300 × 300m² monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

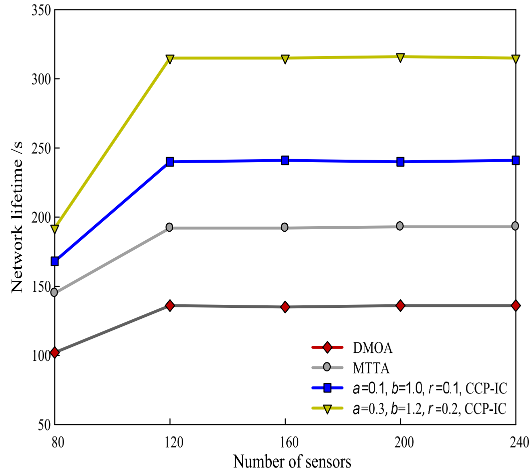


**FIGURE 10.** Network lifetime with 400 × 400m² monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

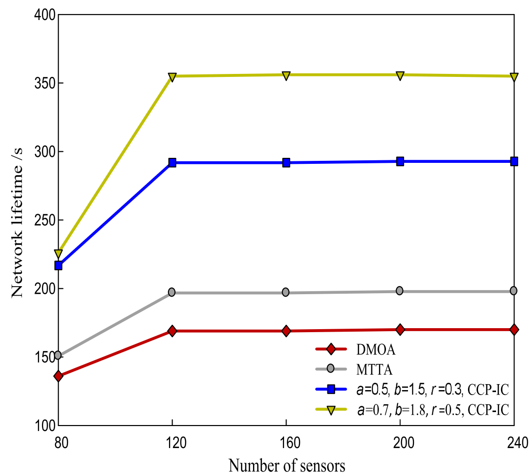


**FIGURE 11.** Network lifetime with 400 × 400m² monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

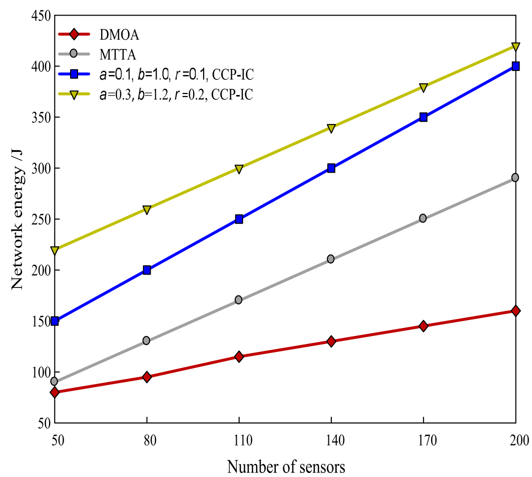


**FIGURE 12.** Network energy with 300 × 300m² monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

behind is that the non-clustering algorithm is adopted by the DMOA algorithm to aggregate the data, which achieves the data collection and communication within the monitoring area at the cost of consuming the energy of the sensor node. Although the MTTA algorithm is based on the clustered structure, the controllable parameter is not introduced to control

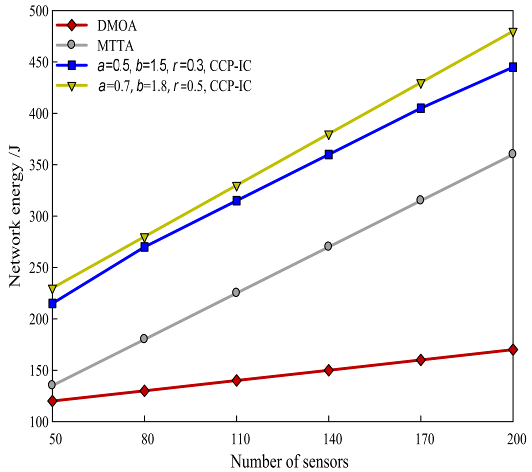


**FIGURE 13.** Network energy with 300 × 300m$^2$ monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

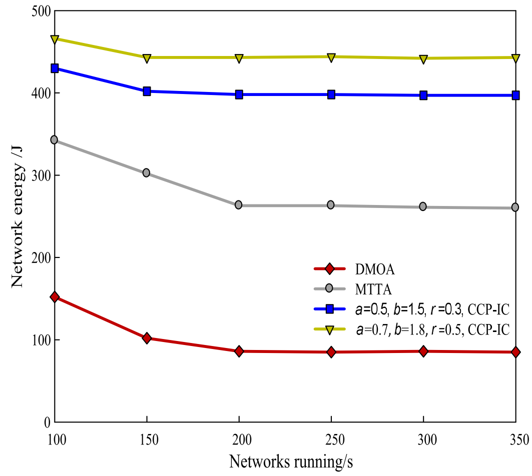


**FIGURE 15.** Network energy against running time with 300 × 300m$^2$ monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

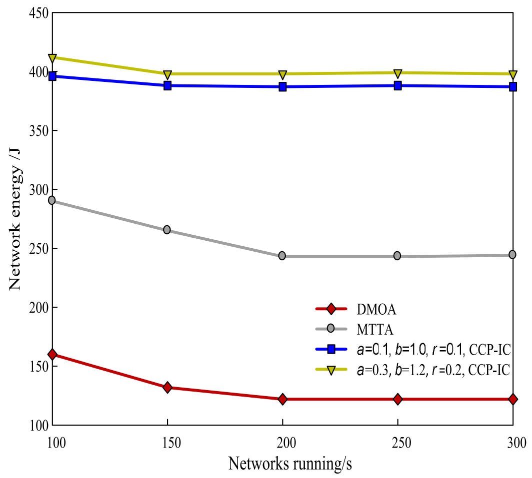


**FIGURE 14.** Network energy against running time with 300 × 300m$^2$ monitoring area and different {$\alpha$, $\beta$, $\rho$} parameters.

the state switching for the nodes, which also leads to rapid exhaustion of the node energy. By contrast, the proposed algorithm employs the controllable parameter to control the node state switching and further controls the aggregation of the data. In terms of the path selection, the configuration can be optimized by controlling the parameters. For the management of the cluster members, the proposed CCP-IC employs the chain to store the information of the nodes while the intelligent ant colony algorithm is used to choose the optimal node as the cluster head for the next hop so that the network energy becomes balanced. The network energy with 300 × 300m$^2$ monitoring area is depicted with increasing running time in Fig. 14 and Fig. 15. Take Fig. 14 as an example, with the increasing time the network energy performances for three algorithms decreasing, and compared with the other two algorithms, the proposed algorithm shows the lowest decreasing rate. The main reasons behind are the fast global update strategy which employs the intelligent ant colony algorithm and the update strategy for local information element. Therefore, the network energy can be effectively controlled. Through the global update strategy, the nodes satisfying the conditions in the chain are compared while the optimal node is chosen as the cluster head in the next period. The node with faster energy consumption is then switched into sleep mode so as to save its energy. The optimal choice on the routing is made according to the update strategy for the local information element so that the optimal path can be found. Consequently, the proposed algorithm could not only prolong the network lifetime but also curb the rapid exhaustion of the network energy.

## VI. CONCLUSION

We mainly studied the dynamic hybrid routing scheme in mobile IoT and proposed an Optimized Clustering Routing Protocol Based on Data Aggregation Controllable Threshold (CCP-IC). This protocol introduced the intelligent ant colony which employs the controllable parameter to achieve distributed clustering of the nodes in the event field. When the event occurs or ends, the Sink calculates the quasi-optimal location according to the obtained event information. The data transmission distance is effectively reduced and the network load is balanced. In order to obtain the new location on time and reduce the unnecessary location calculation, the proposed algorithm utilizes the parameter threshold to determine the related performance information of the nodes in the clustering structure chain. In addition, the CCP-IC algorithm provides a mechanism to re-choose the optimal path, which could guarantee that the cluster head could collect the messages transmitted from the cluster members within a short time and further avoid the data loss in the movement. For the data transmitted in the network, the proposed protocol could achieve the data aggregation within the cluster and the aggregated data can be reliably transmitted. The routing recovery can also be effectively and simply accomplished by the CCP-IC when dead node exists.

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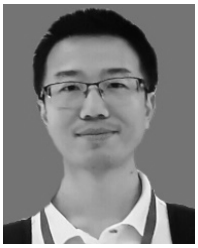

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