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Cluster head selection method of multiple UAVs under COVID-19 situation

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A B S T R A C T
As COVID-19 continues to spread, people are unable to move freely when their residence region is temporarily lockdown, supplies cannot normally enter into such zones, leading to the shortage of supplies in these areas. Thus to ensure the delivery of supplies while reducing contact, the unmanned aerial vehicle (UAV) deliveries have become a common way. In order to efficiently use UAV resources and reduce energy loss in data transmission while performing the tasks, clustering is often used for achieving the above objectives, where the selected cluster heads centrally plan tasks so that reduce the communication times. However, problems such as unreasonable clustering, high energy consumption of cluster heads, and high mortality of cluster heads, directly lead the low cooperation efficiency and short life cycle of UAVs. Considering the nodes often died earlier through the k-means algorithm and ant colony algorithm, and highly dependent on the base station, these factors affect the working cycle and coordination efficiency of the UAVs. Facing the issues above, the cluster head selection algorithm of UAV based on game (CHSA) is proposed, where the mixed game model is adopted to select cluster heads for each region after regional division, and selecting the representative node to perform the cluster head selection algorithm, which help to reduce the energy consumption of each round of communication between nodes. Moreover, the key properties of the CHSA algorithm are proved, and the comparison experiment are conducted to prove the CHSA algorithm can effectively reduce energy consumption and prolong the network life cycle.

1. Introduction
With the continuous development of COVID-19 prevention and control measures, the concepts of prevention and control zones, contained zones and so on are constantly emerging in front of people. Since people cannot move freely in these areas after they are controlled, express delivery cannot enter normally, resulting in the shortage of materials in these areas, poor timeliness of material transportation and high transportation cost. Meanwhile, the entry of transport personnel is highly dangerous and easy to cause epidemic spillover, so the participation of UAVs in delivery becomes the optimal solution. During the epidemic, due to the characteristics of large amount of transportation materials and centralized transportation sites, multi-UAVs cooperation to complete the delivery task has become a better solution.

UAV have a wide range of applications in transportation, agriculture and military. Multi-UAVs cooperation consists of multiple UAVs with certain communication ability and limited energy, and cooperate to complete the task. In recent years, with the continuous improvement of multi-UAVs collaboration technology, wireless sensor networking is developing, moreover wireless sensor network also brings many problems, such as insufficient effective running time of network and high energy loss of sensor in network, which limit the task completion of multi-UAVs cooperation. Based on this, many researchers have proposed clustering algorithms to enhance the effectiveness of multi-UAVs collaboration, among which the low-power adaptive hierarchical cluster routing protocol (LEACH) is a typical representative of multi-UAVs clustering. These protocols are first selected multiple cluster head for multiple UAVs network, and through these clusters first divided into several clusters, cluster head to manage all nodes within the cluster and the base station to send and receive information, and within the cluster nodes and the cluster head to send and receive information, so wireless sensor effectively reduced the average energy consumption, effectively increase the network run efficiently. However, as k-means algorithm, ant colony algorithm and other algorithms are highly dependent on...
base stations, it is difficult for multi-UAVs to cooperate normally in the absence of base stations, leading to the limitations of these algorithms.

Considering game theory mainly focus on game conflicts in the best interest of its own action, for multi-UAVs cluster head selection techniques, game theory is a good way to build this kind of interdependence and environment of the need to maximize their own interests, for multi-UAVs network, the join of game theory to increase the probability of the change of the cluster heads, reducing the probability of each UAV to death, it can effectively prolong the network validity time.

This paper proposes a multi-UAVs cluster head selection algorithm based on game theory, choosing the representative node to perform the algorithm selection, eliminate the dependence of the cluster head selection on the base station, and reducing the communication between nodes in each round that consume energy, and after the whole region is divided into several sub-regions, each subregion adopts the hybrid game model to select the cluster head, which can effectively reduce energy consumption and prolong the network life cycle.

The contribution of our research work can be summarized as following.

1. By replacing traditional base stations with representative nodes, the mobility of UAVs can be improved and is suitable for the situation without base station such as the controlled area. Based on the characteristics of high flexibility and convenient deployment, regional coverage and task diversion can be carried out quickly, and the ability to adapt to environmental changes is stronger.

2. By dividing the task area and selecting the cluster head node on behalf of the node, the energy consumption can be effectively reduced and the network lifetime can be prolonged.

3. Based on game theory, the optimal cluster head selection scheme is realized, which reduces the probability of UAV death and improves the efficiency of UAV mission execution.

2. Related work

The environment and model of multi-agent collaboration is constructed [1], and it proposes the effectiveness of multi-agent collaboration. Xue Hongtao, etc. [2] introduce a variety of different modes of multi-agent cooperation, and analyzes and compares the advantages and disadvantages of the three modes. Hu Gang, etc. [3] introduce the LEACH protocol and points out that clustering algorithm can effectively prolong the life cycle of wireless sensor networks. Various forms of clustering algorithms are analyzed and it proves the effectiveness of clustering algorithm from the perspective of energy balance and network life cycle [4]. In addition, it is pointed out that the advantages and disadvantages of a clustering algorithm are mainly measured by the following criteria: the stability of cluster structure, the number of cluster head nodes, and load balancing degree [5].

Cheng Xuezhen, etc. [6] state an optimization combinatorial weighting algorithm and an improved ant colony optimization algorithm were proposed to dynamically change the nodes in different regions of weight and optimize the LEACH protocol. With the combination of the ant colony algorithm, a multi-parameter weighted energy-saving clustering routing protocol is proposed, which can significantly prolong the network life [7]. Moreover, the multipath routing protocol that combines the clustering mechanism and ant colony algorithm, is used to improve pheromone concentration factor and heuristic function factor by considering remaining energy and the number of neighbor nodes [8]. Cheng Xuezhen, etc. [6] combine local and global pheromone updating mechanisms to update transmission paths between clusters through the dynamic replacement mechanism of cluster-head nodes in the whole network. Lu Daogang, etc. [9] present that an algorithm based on improved K-means and non-uniform clustering routing algorithm in optimizing the structure of the clusters, cluster optimization phase by introducing based on distance and weighted average remaining energy evaluation function to optimize the initial clustering of the improved algorithm can effectively solve the problem of “hot spots” balanced network energy consumption and prolong the network life cycle. Fang Shengwang, etc. [10] use the improved K-means clustering routing protocol algorithm based on the distance between nodes, and introduces energy factor, centroid factor and distance factor to improve the quality of selected cluster heads. Besides, in order to solve the problem of energy imbalance caused by random clustering and uneven clustering in LEACH algorithm, the routing algorithm of uniform clustering is proposed [6].Wang Gaiyun, etc. [11] use hierarchical clustering and chaotic algorithm and evaluation function to optimize the selection of cluster head. Liu Jing, etc. [12] proposed a cluster head selection algorithm based on the number of cluster notes on the basis of the classical algorithm LEACH. And, particle swarm optimization fuzzy C-means was used to overcome the sensitivity to the initial clustering center, and the cat swarm optimization algorithm was used to find the optimal routing path of the cluster head, so as to balance the load of the cluster head without increasing the load of relay nodes [13]. The cluster head calculation method and clustering algorithm combining gaussian distribution function and genetic algorithm is proposed to optimize the fitness function and improve the selection of next hop nodes [7]. The behavior of sensor nodes in the network is simulated through the hybrid strategy model, and the nodes continue to play games until the revenue function maximizes to reach the game equilibrium [14]. However, the above algorithms often depend on the existence of base stations, the cooperative task of multi-agent cannot be accomplished if there is no base station.

3. Modeling and analysis

3.1. Problem analysis

Assuming there are \( n \) UAVs need to go to the controlled community A to perform the delivery of supplies for the residents as shown in Fig. 1, and community A is the square region of \( k \times k \), and each round has a different number of delivery tasks as shows in the right side of Fig. 2. Supposing that in the first round, in order to complete \( T \) tasks the UAVs received, it needs to select representative UAV to perform cluster head selection algorithm and divide UAVs into \( T \) groups. Next, each UAVs group needs a cluster head to complete the task assignment, other UAVs within the group receive tasks from the cluster head as shows in the middle of Fig. 2, and the cluster head sends the task completion situation to the representative UAV after fusion processing, and completes the multiplexing scheduling among the UAVs within the group. When \( t \in T \) cluster head UAVs are found, other UAVs are grouped according to the remaining energy and distance as shows in the right side of Fig. 2. When completing the task, UAVs will consume energy until the task stops when all the energy of UAVs are exhausted. Fig. 1. Schematic of the delivery of supplies by UAVs.
3.2. Model hypothesis

(1) This model assumes that UAVs positions are randomly assigned within a square network area.
(2) All UAVs have the same ability to transmit, receive, and complete missions.
(3) The transmission lines between any two UAVs are completely consistent, that is, the direct information transmission between two UAVs is completely consistent.
(4) All UAVs positions do not change at the beginning of each round, and the UAV returns to its original position after completing the mission.
(5) The UAV's energy is virtually divided into two parts, one for communication and the other for mission completion.

3.3. Modeling

3.3.1. Energy loss model

Referring to the wireless communication energy consumption mode in the Leach model [15], denote the task area as a square area of \( k \times k \). In the communication between nodes, the energy consumption of sending and receiving data per unit bit is as follows:

\[
E_{s}(l) = \begin{cases} 
1 \times E_{elec} + 1 \times \epsilon_{fs} \times d^2 & d < d_0 \\
1 \times E_{elec} + 1 \times \epsilon_{mp} \times d^4 & d \geq d_0 
\end{cases}
\]

Where \( E_{elec} \) represents the energy consumption of node to send or receive data per unit bit, \( d \) is the distance between the communication nodes, \( \epsilon_{fs} \) and \( \epsilon_{mp} \) represents the energy coefficient required for power amplification under free-space energy consumption model and multipath weak channel model respectively. And \( d_0 \) is the critical distance value, where:

\[
d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (2)
\]

3.3.2. Representative node model

Since there is no base station in this paper, it is necessary to select a representative node for each round of tasks to perform cluster head selection algorithm, assign tasks, receive task completion information and find out the representative node for the next round. Also due to the representative node works the most heavily and consumes the most energy in each round, we select the node with the largest energy in each round as the representative node, that is, the representative node we select is \( \text{Energy}(x_i) \geq \text{Energy}(x_j) \) where \( i \in (1, n) \). Thus the energy consumed by the representative node in each round is:

\[
E_{rp} = 2 \times E_{th} + E_{amp}
\]

Thus the energy consumed by the representative node is:

\[
E_{th} \text{ represents the energy consumed in communicating with the cluster head, and is used for task sending and receiving results, thus it is needed to communicate twice.} \;
E_{amp} \text{ states the amount of energy required to pass information from all nodes to the next representative node.}
\]

3.3.3. Game model

The index to evaluate whether the game strategy is reasonable is the utility function, and the participants change their strategies according to the information they acquire. The strategy set is the combination of the possible strategies of all nodes when they obtain their maximum expected utilities, that is, the game equilibrium is reached.

Assuming all nodes (UAVs) are finite rational subjects and aim to maximize their own utilities in the cluster forming game of whether nodes declare to participate in the cluster-head selection. And there are two strategies in the node’s strategy space \( D, N_D \), where \( D \) denotes the strategy that the node declare to be the head node, while \( N_D \) denotes the node does not to declare to be the head node. If no node declares itself as a candidate cluster head, the task fails and all nodes get 0 returns as the utility and \( U = 0 \). If any node is declared as the cluster head, the utility of all nodes is \( U = A \), and the utility of the cluster head node is \( A \) minus the cost of becoming the cluster head \( B \), thus the utility is \( U_h = A - B \), and the game matrix can be obtained as shows in Table 1.

According to the above analysis, we can conclude for the clustering game involving \( N \) nodes, for any node \( i \in N \)’s utility is:

\[
U_i = \begin{cases} 
0 & \text{if } s_i = N_D, \forall i \in N \\
A - B & \text{if } s_i = D \\
A & \text{if } s_i = N_D \land \exists \in N, s_j = D
\end{cases}
\]

In order to achieve Nash equilibrium, nodes need to adopt a mixed strategy to declare themselves as cluster heads, that is, nodes randomly participate in the cluster head game according to the equilibrium probability. If the node is selected as the cluster head, the probability is \( P \), and the probability of not choosing to be the cluster head is \( Q = 1 - P \).

\[
P = 1 - \omega \frac{N-1}{N} \quad (5)
\]

Where \( \omega = \frac{B}{A} < 1 \).

3.4. Problems analysis

Table 2 shows the main parameters and descriptions involved in this paper.

Under the epidemic situation, there are containment areas, and it is difficult for people to obtain supplies, and the delivery of goods by UAV can reduce people’s contact. As shown in Fig. 3, assuming that there are two containment areas, and there are a total of 10 UAVs to perform tasks, which are grouped into clusters and then go to the
4. Description of algorithm

4.1. Clustering algorithm based on game

The algorithm input is the UAVs sequence and task sequence, $AgentSequence = \{x_1, x_2, ..., x_n\}$ and $TaskSequence = \{y_1, y_2, ..., y_n\}$, where $x_i = (p_i, q_i, energy_i, energy_j)$, $p_i$ denotes the horizontal coordinate of the UAVs, $q_i$ represents the vertical coordinate of the UAVs, $energy_i$ is the remaining energy of the node communication battery, and $energy_j$ is the remaining energy of the node task battery. When tasks are received, the region is divided into $k$ partitions according to the number of tasks.

In the first round, all the nodes exchange information with each other, so there are $k$ UAVs, and each node needs to exchange information with other nodes, and the total times of information transmission required is $k \times (k - 1)$. Next, the UAV $x_i$ with the highest energy was selected as the representative agent according to the energy intensity, that is $x_i.energy \geq x_j.energy$, where $i \in [1, n]$, $x_i$ is the representative node of the first round. The probability of claiming a cluster head in each partition is then calculated as $P_k(i) = \frac{E_{res}(i)}{\sum_{i=1}^{n} E_{res}(i)}$, and $\omega = \frac{B}{4} \times N_t$, $N_t$ is the number of UAVs alive in the zone, and in the case of the remaining effective drone power is generally low, we have that $P_k(i) = \frac{E_{res}(i)}{\sum_{i=1}^{n} E_{res}(i)} \times (1 - \omega N_t)^{-1}$, where $E_{res}(i)$ is the remaining energy of the UAVs, $E_{res}(i)$ is the average remaining energy of UAVs in this area. Assuming that there are multiple candidate cluster heads in the area $k$, the energy distance ratio factor of each candidate cluster head is calculated as $\frac{E_{res}(i)}{d(i, obst)}$ and $d(i, obst)$ is the distance between this node and the representative node. The candidate cluster head with the largest energy-distance ratio factor was selected to be the real cluster head, and the other UAVs joined each cluster head according to the distance to each cluster head and their own energy and other information to form clusters. The cluster head node tells the representative node the energy information of other nodes in the cluster, and finally, the representative node selects the representative node for the next round according to the information of all nodes, and the input of the algorithm in the next round is the UAVs sequence, and the output is the clustering result of UAVs sequence. The detailed algorithm is shown as Algorithm 1.

The proposed CHSA algorithm is designed to be applicable to the distribution and execution of tasks such as UAVs material delivery without base station under the COVID-19 situation. And the goals are to improve the survival rate of nodes, save energy consumption and make the execution of UAVs tasks more flexible. Table 3 compares the application conditions of CHSA algorithm and other two mainstream algorithms, the ant colony algorithm and K-means algorithm. Although some algorithms have been improved based on the two algorithms [16, 17], the most common algorithms for cluster head selection without base station are ant colony algorithm and K-means algorithm [18], and the comparison of these algorithms in node survival rate, energy consumption and other attributes are detailed in Section 5, and will not be repeated here.

Algorithm 1 Cluster head selection algorithm of UAV based on game

Input: $AgentSequence = \{x_1, x_2, ..., x_n\}$, $TaskSequence = \{y_1, y_2, ..., y_n\}$

Output: UAVs clustering sequence $q$

1: for i in rank k do
2: for i in Agent sequence do
3: Find the node with the highest energy $x_i$, and set $x_i$ as the representative node.
4: end for
5: for each partition do
6: if a large number of viable nodes exist then
7: $p_k(i) = \omega \sqrt{\frac{1}{E_{avg}}}$
8: else
9: $P_k(i) = \frac{E_{res}(i)}{d(i, obst)} \times (1 - \omega N_t)^{-1}$
10: All nodes enter the candidate cluster head queue according to probability
11: end if
12: end for
13: for each partition do
14: $max \leftarrow 0$
15: Calculate the energy distance ratio of each candidate cluster head $\frac{E_{res}(i)}{d(i, obst)}$
16: if $\frac{E_{res}(i)}{d(i, obst)} > max$ then
17: $max \leftarrow \frac{E_{res}(i)}{d(i, obst)}$
18: The node corresponding to max becomes the real cluster head
19: end if
20: end for
21: for other UAVs do
22: UAVs join the nearest cluster head to form cluster
23: end for
24: When the task is complete, the information is sent back to the representative node
25: The representative node selects the representative node of the next round and exchange information
26: end for

4.2. Proof of properties

4.2.1. Proof of time complexity

Theorem 1. The time complexity of the CHSA algorithm is $O(ntk)$

Proof. Firstly, there are four cycles in the CHSA algorithm. In the first loop, we need to facilitate the entire UAV queue to find the point with the maximum energy to become the representative node, and it needs to traverse all the nodes $n$ times, thus the time complexity is $T_1(n) = O(n)$. And in the second loop, it is needed to firstly traverse all the nodes
which costs \( n \) times in total to calculate the probability of becoming the cluster head, and the time complexity is \( T_2(n) = O(n) \). While in the third loop, all partitions need to be traversed and it takes \( t \) times in total, and the node with the greatest distance ratio should be found as the cluster head in each partition, and it takes \( n \times t \) times on average, therefore the time complexity is \( T_3(n) = O(n \times t) \). In addition, in the last loop, all nodes need to be traversed and it takes \( n \) times, and it is needed to add all nodes except the cluster head node to the nearest cluster head which costs \( t \times n \) times for forming the cluster, and the time complexity is \( T_4(n) = O(n \times t) \). Therefore, the time complexity of one round of CHSA algorithm is \( T = T_1(n) + T_2(n) + T_3(n) + T_4(n) = O(n \times t) \), and a total of \( k \) rounds are needed to calculate the cluster heads of UAVs in each round to form clusters to complete the task, thus the total time complexity of the CHSA algorithm is \( T_{CHSA} = O(n \times t) \times O(k) = O(n \times t \times k) \), where \( n \) is the number of objects in the dataset, \( t \) is the number of iterations of the algorithm, and \( k \) stands for the number of clusters.

4.2.2. Proof of feasibility

**Proposition 1.** Assuming there is a finite set of UAVs need to form \( m \) clusters, with the same UAV sequence as the input of the CHSA algorithm, it can output \( m \) stable clustering results, that, the algorithm is feasible.

**Proof.** The clustering process is dynamically simulated in Fig. 4, where the asterisk represents the nodes, which transmits information to the cluster-head node, which is represented by the square node. And the common nodes represented by the circular nodes are added to form clusters according to the energy distance ratio. The proposed algorithm can complete the clustering process according to the input tasks, and form clusters to complete the cooperation tasks of multiple UAVs.

4.2.3. Special cases

In Fig. 5, the performance of the algorithm with the existence of energy maxima is simulated. Ten energy maxima points are set. After the selection of cluster heads based on game, most of the energy maxima points eventually become cluster heads. It indicates that the proposed game algorithm has better performance, and can obtain better solution.

5. Experimental results

5.1. Experiments settings

In this section, we use Python to analyze and compare the performance and effects of the three algorithms. The software environment is Pycharm Community 2021.2.4 and Python3.10, and the hardware environment is Lenovo Y7000P and Windows10.

We randomly deploy 100 sensor nodes in the 100*100 m region to simulate the algorithm performance of the same network scale. Table 4 shows the specific simulation parameters.

5.2. Comparison of algorithm running time

Fig. 6 is a comparison of algorithm running time. The abscissa is the running rounds and the ordinate is the consumed time. By comparing with the CHSA algorithm, ant colony algorithm and K-means algorithm, it can be seen that when there are more running
rounds, ant colony algorithm consumes significantly lower time. The CHSA algorithm has no dependence on base station due to the addition of representative node mechanism, and the time is slightly longer than K-means algorithm, but the consumption time is not different.

5.3. Average energy comparison of remaining nodes

Fig. 7 shows the comparison of the average energy of remaining nodes. The abscissa is the running rounds and the ordinate is the average remaining energy of surviving nodes. By comparing the CHSA algorithm, ant colony algorithm and K-means algorithm, it can be seen that the average energy of the remaining nodes of the CHSA algorithm is higher than that of the other two algorithms, that is, the average energy consumption per round is less.

5.4. Comparison of the number of remaining nodes

Fig. 8 is the comparison of the number of remaining surviving nodes. The abscissa is the number of running rounds, and the ordinate is the number of remaining surviving nodes. By comparing with the CHSA algorithm, ant colony algorithm and K-means algorithm, it can be seen that the ant colony algorithm has a short life cycle, and the death nodes increase quickly and arrive early. However, the remaining surviving nodes of the CHSA algorithm and K-means algorithm are basically the same when the number of rounds is small, and the number of surviving nodes of the CHSA algorithm is slightly higher than that of K-means algorithm when there are more rounds.

5.5. Performance of CHSA algorithm under different initial conditions

Figs. 9 and 10 show the clustering results under different initial conditions with CHSA algorithm, and the experimental results show that the CHSA algorithm can divide UAVs into suitable clusters as required to perform tasks under different number of nodes and cluster head nodes, which indicates that the CHSA algorithm is generic to all kinds of different conditions.

5.6. Summary of algorithm comparison

Both ant colony algorithm and K-means algorithm are commonly used for router clustering. Under the same experimental conditions, based on the above comparative experiments, we can find that ant colony algorithm has the highest efficiency, however, its performance is far inferior to the other two algorithms, that is, its lifetime is short and the average energy of remaining nodes is less. In comparison, the efficiency of CHSA algorithm and K-means algorithm is almost the same. CHSA algorithm cannot rely on the operation of the base station, which can prolong the algorithm life cycle, reduce the energy consumption, which is better than K-means algorithm. And the comparison results are shown in Table 5.

6. Conclusion

In this paper, a multi-UAVs clustering algorithm is proposed to solve the problem of supplies supply in the containment area due to the COVID-19. Considering the problems of the current clustering algorithm involving the high dependence on base stations, and short life cycle of common algorithms, etc., a multi-UAV cooperative clustering algorithm based on game algorithm is proposed and designed, where using the mixed game strategy to select cluster heads and selects representative nodes that to solve the problems when there is no base
station, and can effectively reduce transmission energy consumption of representative nodes. At the end of each round of task performance, the representative nodes will elect a new representative node and transmits the information to the next representative node. Moreover, through the experimental results, it proves that the proposed CHSA algorithm can effectively reduce energy consumption, prolong the network life cycle, and the base station is not needed for completing the task.

However, there are some limitations of the research work in this paper, which is reflected in that the heterogeneity of UAV load is not taken into consideration. Therefore, in the future, the impact of the carrying capacity of UAV on the distribution of supplies on clustering should be further studied.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] Y. Yang, X. Li, X. Xu, A survey of technology of mutiagent cooperation, Inf. Control 04 (2001).
[2] H. Xue, Y. Ye, L. Shen, W. Chang, A review on architecture and coordination mechanism of multi-agent systems, Robot 01 (2001) 85–90.
[3] G. Hu, D. Xie, Y. Wu, Research and improvement of wireless sensor network routing protocol LEACH, J. Sens. Technol. 06 (2007) 1391–1396.
[4] J. Xu, X. Zhang, B. Xu, Z. Sun, Review of clustering algorithms in wireless sensor networks, Comput. Sci. 44 (2017) 31–37.
[5] G. Hu, J. Jiang, Z. Gong, Review of clustering algorithms for mobile ad hoc networks, Comput. Eng. Science 01 (2005) 49–50.
[6] X. Cheng, C. Xu, X. Liu, J. Li, J. Zhang, LEACH protocol optimization based on weighting strategy and the improved ant colony algorithm, Front. Neurorobotics 16 (2022).
[7] P. Wang, Research on clustering routing based on genetic algorithm and ant colony algorithm in wireless sensor networks, 2021, Jilin University.
[8] Y. Jin, H. Zhu, Multipath routing protocol for wireless sensor networks based on clustering and ant colony, J. Zhejiang Norm. Univ. 42 (2019) 400–406.
[9] D. Lu, Q. Li, J. Sun, Non-uniform clustering routing algorithm based on improved K-means and cluster structure optimization, Transducer Microsyst. Technol. 39 (2020) 144–147.
[10] S. Fang, L. Wan, Z. Hu, Routing algorithm for wireless sensor networks based on distance metric clustering, Comput. Eng. Des. 42 (2021) 3316–3322.
[11] G. Wang, J. Liu, J. Shen, B. Zhang, C. Sun, Z. Guo, Improved routing protocol algorithm based on hierarchical clustering, in: J. Phys.: Conf. Ser., 2216, (1) IOP Publishing, 2022, 012072.
[12] J. Liu, S. Su, A cluster heads selection algorithm of wireless sensor network based on cluster notes number, in: Proceedings of the 11th International Conference on Computer Engineering and Networks, Springer, 2022, pp. 1250–1259.
[13] S. Su, S. Zhao, An optimal clustering mechanism based on fuzzy-C means for wireless sensor networks, Sustain. Comput.: Inform. Syst. 18 (2018) 127–134.
[14] B. Wang, Y. Xia, S. Zhao, Clustering routing algorithm for wireless sensor network based on mixed strategy game theory, Sensors Mater. 34 (2) (2022) 885–896.
[15] C. Wang, Z. Xu, Research on clustering routing algorithm based on game theory in wireless sensor networks, J. Wuhan Polytech. Univ. 40 (2021) 51–56.
[16] M. Sivaguru, M. Punniyamoorthy, Performance-enhanced rough k K-means clustering algorithm, Soft Comput. 25 (2) (2021) 1595–1616.
[17] T.D. Khang, M.-K. Tran, M. Fowler, A novel semi-supervised fuzzy C-means clustering algorithm using multiple fuzzification coefficients, Algorithms 14 (9) (2021) 258.
[18] X.Z. Wang Chang, Game oriented clustering routing algorithm for WSN, J. Wuhan Polytech. Univ. 40 (2021) 51–56.