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The application of intelligent data analysis methods for traffic processing in a wireless sensor network

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ABSTRACT

Wireless sensor networks (WSNs) enable the collection and transmission of data in the Internet of Things (IoT), and are widely used in various sectors, such as the military, industrial, agricultural, environmental, transport, social and medical sectors. WSNs are networks that provide continuous communication and access to information at any time and in any place. The main areas of research in this work relate to the application of intelligent data analysis methods to improve data transmission characteristics and quality of service in a heterogeneous wireless sensor network, which consists of a ground segment with stationary sensor nodes and an aerial network; this is an extremely pressing challenge in the monitoring and control of coverage areas using the Internet of Things. This paper investigates a method for efficient clustering in a ground-based wireless sensor network, which ensures the identification and allocation of an optimal number of clusters and the designation of primary cluster nodes, thereby ensuring efficient processing and transmission of traffic across different network segments. Approaches have been proposed and are continuing to be developed that combine various methods of cluster formation and data transmission between nodes of different topological types. Data can be sent from an end node directly to the base station, via a primary cluster node, or via a sequence of such nodes before reaching the base station. In solving the tasks set, methods from graph theory, artificial neural networks, genetic algorithms and K-means, as well as software engineering, were utilized.

Keywords: algorithm; data analysis; artificial intelligence; Internet of Things; method; cluster node; clustering; traffic; neural network; wireless sensor network; software engineering

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Relevance of the research topic. At present, the development and implementation of new systems and devices incorporating elements of artificial intelligence across all sectors of the national economy is a priority area of scientific research. The 21st century is the era of the Internet of Things (IoT), both in industrial and social contexts, with the daily application of a range of methods and technologies for intelligent data analysis.

The IoT architecture comprises four layers: the sensor and sensor network layer, the gateway and network layer, the service layer and the application layer. The base layer consists of low-speed wireless sensor networks (WSNs) based on several standards.

Technological progress, linked in particular to the application of intelligent data analysis methods, has spurred the emergence of new types of WSNs, such as flying networks, swarm robotics, the tactile internet, and intelligent telecommunications services [1], [2].

In this context, the use of heterogeneous networks is promising; these integrate segments of a ground-based network comprising stationary sensor nodes with wireless sensors with an aerial network of low-cost unmanned aerial vehicles for transmitting data over long distances to a base station for processing.

Given the limited resources of UAV-based communication systems in particular, power, the protocols and algorithms used in such systems, the choice of how to organize information memory

and data transmission speed which directly influence the development and testing of transmission is one of the key challenges during the design of UAV-based communication systems.

With a view to enhancing the efficiency of WSNs and improving Quality of Service (QoS) metrics, it is advisable to investigate the application of modern intelligent technologies that will enable the transmission of information in distributed networks even in cases of partial degradation or integrity breaches [3].

In this regard, comprehensive automated monitoring is being implemented using wireless sensor network technologies and unmanned aerial vehicles. Within the coverage area, a specified number of fixed sensors required for detailed monitoring are deployed; these transmit information via an air corridor through which unmanned aerial vehicles (UAVs) operate, linking a ground gateway in a fertile area of mountainous terrain and a base station to the Internet of Things (IoT) control center.

Aims and objectives of the research. The aim of this work is to improve the efficiency of the UAS by applying methods and algorithms of intelligent analysis during the collection and routing data in a heterogeneous UAS network that integrates a ground-based network with stationary sensor nodes and an aerial sensor network. To achieve this aim, two tasks are addressed in this study. First: to investigate methods, algorithms and the software tools that implement them, relating to the Quality of Service (QoS) of the UAS network. To develop a mathematical model of a heterogeneous wireless sensor network that ensures efficient processing and transmission of traffic across different network segments. Second: to investigate a method for efficient clustering in a ground-based wireless sensor network, which ensures the determination and allocation of the optimal number of clusters and the designation of primary cluster nodes (PCNs).

Problem formulation. To implement traffic optimization tasks in a heterogeneous wireless sensor network comprising two segments – a ground-based wireless network with stationary sensor nodes and an aerial UAV network – a number of intelligent artificial network (IAN) methods are employed. The approach is based on the use of a radio visibility matrix. For the ground segment, the Kohonen network and Constructive Modified K-Means methods are used for clustering and routing, in conjunction with *the* Hopfield neural network *model*; whilst for the UAV corridor, Dijkstra's algorithm and a genetic algorithm are employed.

Sensors measuring carbon dioxide, soil moisture, temperature, air humidity and precipitation are randomly distributed within the ground segment; each sensor is equipped with a GPS (Global Positioning System) unit to determine its location, and each sensor has a range of 100 meters (Fig. 1). Data is transmitted between sensors using the IEEE 802.15.4 standard and the Zigbee protocol, which utilizes this technology and provides a transmission rate of 20 to 250 kbit/s over a distance of 1 to 100 meters. The information collected by the ground-based network is transmitted via a gateway to a swarm of UAVs, where the data is routed and subsequently transmitted to the base station.

Radio visibility matrix of WSN nodes. Based on the arrangement of the sensors and their detection range, a WSN radio visibility matrix can be derived, which defines the communication mechanism between the sensors, i.e. identifies which sensors are physically connected to one another.

If a neighbour is outside a node's coverage area, it is assigned a value of 0.

If a neighbour is within a node's range, proximity is determined by calculating the distance between the node and its neighbour.

Mathematically, the radio visibility matrix is described as follows:

$$\vec{P}_t \in Z_i = \{p\} \in \{z\} = p_1 \in z_1, \dots, p_j \in z_j, \dots, p_L \in z_L, \quad (1)$$

$$\forall q_i \exists Z_i \in q_i: (p_1 \in z_1, \dots, p_j \in z_j, \dots, p_L \in z_L) \in q_i. \quad (2)$$

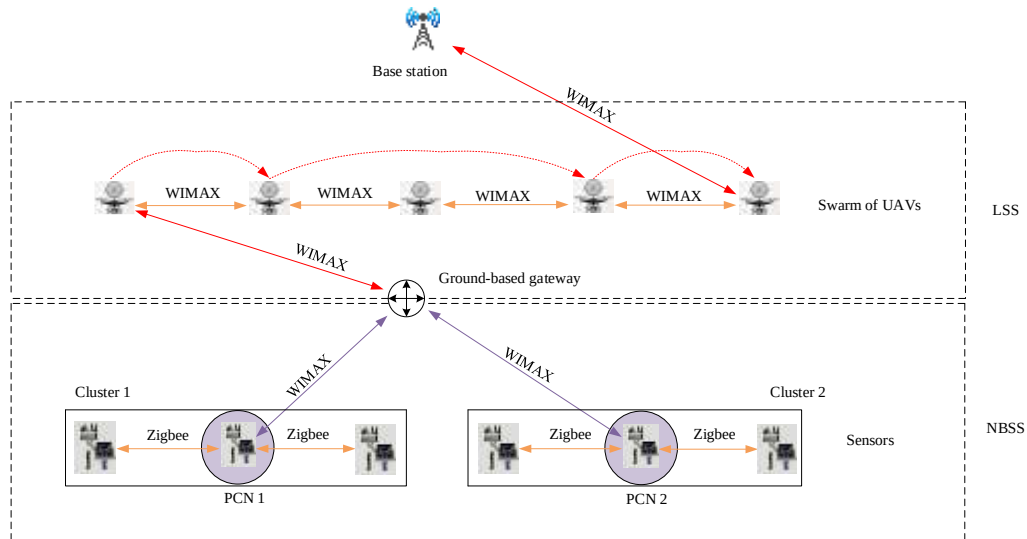


Fig. 1. Model for a heterogeneous wireless sensor networks
Source: compiled by the authors

Thus, the connections between nodes and the line-of-sight visibility of each node relative to the other nodes can be modelled using the so-called line-of-sight visibility matrix P .

$$P = \begin{bmatrix} 100 & P_{12} & \dots & P_{1j} & \dots & P_{1n} \\ P_{21} & 100 & \dots & P_{2j} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ P_{i1} & P_{i2} & \dots & 100 & \dots & P_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nj} & \dots & 100 \end{bmatrix}, \quad (3)$$

$$P_{ij} = \begin{cases} P_{ij}, & \text{if } i \neq j \\ \text{otherwise } 100, & P_{ij} \in [0 \dots 100] \end{cases}$$

The first line indicates the radio visibility of the first node in relation to the other nodes. The second line indicates the radio visibility of the second node in relation to the other nodes, and so on.

Based on an analysis of modern methods and algorithms for transmitting and processing information in a WSN, there are several types of routing protocols.

Design of a Kohonen network training algorithm. There are various methods for organizing data transmission in a WSN, but clustering is predominantly used, as it plays a major role in routing data to the base station by identifying the cluster centers that transmit data. This reduces the number of data transmission paths and lowers the load on the network. One effective method of reducing the power consumption of sensor nodes and the WSN is clustering, which helps to extend the WSN's operational lifetime [5].

During the clustering process, the following tasks must be addressed:

- 1) determining the set of cluster objects (groups of WSN considered as traffic sources);
- 2) determining the properties of the clustering objects (the location of the nodes, i.e. their coordinates in two- or three-dimensional space and their radio visibility);
- 3) determining the purpose of clustering (defining the structure of the access network, i.e. selecting the coordinates of the main cluster nodes (MCNs), which are treated as intermediate nodes for access to the gateway);
- 4) determination of the cluster selection criterion – the requirements or conditions for separating network nodes to assess the similarity of object characteristics within the formed clusters, such as: the maximum number of clusters, cluster size, the number of nodes in clusters, and others (in our case, a specified number of clusters is selected).

One of the clustering methods selected for this study is based on the Kohonen network learning

algorithm using the Constructive Method [6] and is founded on the representation of nodes as a radio visibility matrix P according to formula (3). In this algorithm, the signal strengths (RSS) of each node's neighbours are assigned to that node in the radio visibility matrix.

Once the radio visibility matrix P has been formed, it must be normalized using the following formula:

$$P_{NORM} = \frac{P}{P_{max}}, \quad (4)$$

where $P_{max} = 100$

The *NET* network used for clustering depends on the following parameters:

$$NET(N, K, \alpha_0, \tau, R, \varepsilon, \{L\}), \quad (5)$$

where N is the number of input neurons, equal to the number of network nodes; K is the number of output neurons, equal to the number of clusters; α_0 is the initial value of the learning rate; and decreases over time; τ is the learning time constant; R is the sensitivity radius; ε is the learning accuracy; $\{L\}$ is the training sample, equal to P_{NORM} .

Using these parameters, cluster formation using the constructive method proceeds as follows and consists of six stages:

- 1) the rows of the radio-visibility matrix are fed as training vectors into the neural network;
- 2) in the case of the first operation of the neural network, there is only one neuron, and its weights are initialized with the values of the first row of the radio visibility matrix; the process then proceeds to step 1, otherwise it proceeds to step 3;

The Euclidean distance is calculated using formula (6) between the current input vector and the weights of each neuron, and then the smallest distance is selected, which represents the winning neuron (or cluster) for the current input vector.

$$d(x, w_i) = \|x - w_i\| = \sqrt{\sum_{j=1}^n (x_j - w_{ij})^2}, \quad (6)$$

$$d(x, w_i) \leq \sqrt{NR}, \quad (7)$$

- 1) If the Euclidean distance between the winning cluster and the input vector (x, w_i) does not satisfy condition (7), then a new neuron will be added to the neural network, and its weights will be the values of this input vector, followed by a return to step 1.

- 2) The weights of the winning cluster and the learning rate are adjusted using formula (8).

$$w_i^{t+1} = w_i^t + \alpha(t) \cdot (x - w_i^t), \quad (8)$$

where w_i^t is the weight vector of the i -th neuron; t is the training iteration number; x is the input vector; $\alpha(t)$ is the learning rate.

$$\alpha(t) = \alpha_0 \cdot \exp\left(-\frac{t}{\tau}\right) = 0.7 \cdot \exp\left(-\frac{t}{1000}\right). \quad (9)$$

- 3) If the current training vector is the last one, and if the weights of each neuron change by more than ε compared to the previous case (the final weight matrix will not change at each training iteration if the weights of each neuron change by less than ε), then the training of the neural network is terminated; otherwise, the process returns to step 1, and training resumes from the first training vector.

Effective clustering. Below a method the method for the effective clustering of a terrestrial wireless sensor network using a modified K-means algorithm, taking into account radio visibility zones and the GPS coordinates of nodes, which allows the number of clusters to be optimized and prevents the 'clustering' of wireless sensor nodes in a small area of the coverage zone. The effectiveness of clustering ultimately depends on finding the optimal number of clusters in the network.

To achieve this aim, the author has modified the basic K-means algorithm as follows [7]:

Stage 1. The initial number of clusters is determined using formula (10), based on the shape of the survey area (square area), the radio propagation model (free space) and the number of nodes distributed within the survey area [8].

$$K_{opt} = \sqrt{\frac{3*N}{\pi}} = 0.977 * \sqrt{N}, \quad (10)$$

where N is the number of nodes.

Stage 2. The drawback of random initialization of cluster centers (GKV) is overcome by determining the initial virtual points of the cluster centers on a circle, as shown in Fig. 2, in accordance with formula (11):

$$\begin{aligned} \theta &= \frac{2*\pi}{K_{opt}}, \\ X_{PNC} &= R * \cos(\theta * k), \quad k = 1, \dots, K_{opt}, \quad R = \frac{L}{4}, \\ Y_{PNC} &= R * \sin(\theta * k), \end{aligned} \quad (11)$$

where K_{opt} is the optimal number of clusters; L is the length of the sensor field; θ is the angle defining the distance between the GKV's on the circle; R is the radius of the circle, equal to a quarter of the length of the sensing zone.

This approach avoids the ‘clustering’ of PCNs within a small area of the coverage zone. To determine the PCN, it is necessary to find the nodes closest to the center points of each cluster. Then, within each cluster, it is necessary to ensure that all nodes in the cluster are within the range of a PCN node.

Stage 3. Identify the nodes belonging to each cluster, as in stage 2 of the basic K-means algorithm. Nodes that are not within the radio visibility range of any PCN send their data directly to the base station;

Stage 4. The algorithm for finding the node closest to the cluster center and designating it as the PCN is executed using the Euclidean distance.

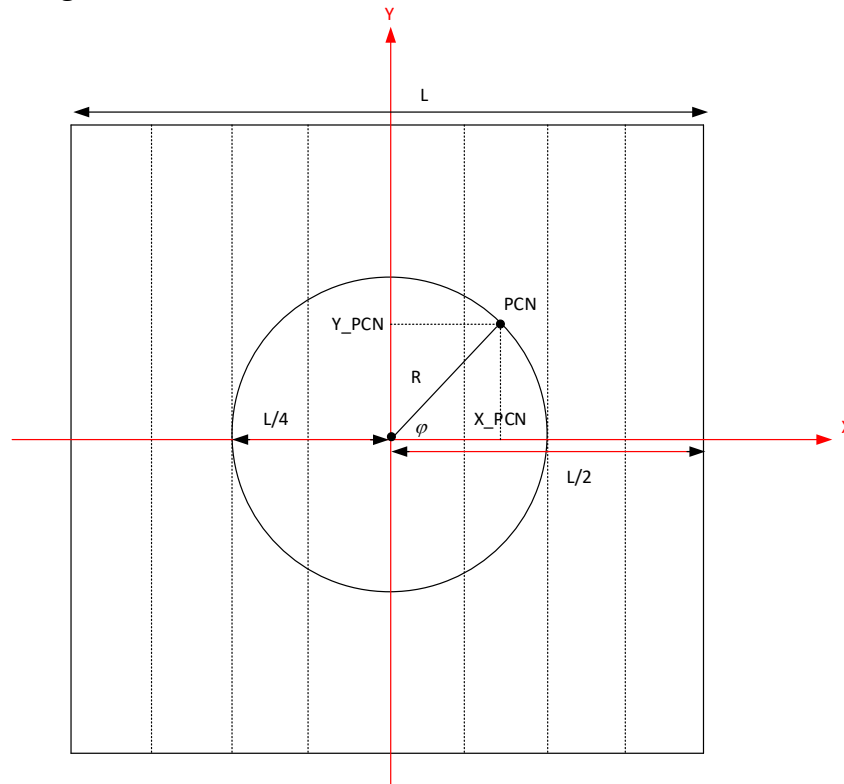


Fig. 2. Distribution of PCN around the circumference

Source: compiled by the authors

Fig. 3 shows a flowchart of the modified K-means algorithm. The initial parameters are specified at the input; then the optimal number of clusters K_{opt} is determined using formula (10), and test experiments are carried out to validate the values used; subsequently, the initial coordinates of the cluster centers μ_k on the circle are initialized using formula (11). Inside the loop, the Euclidean distance $p(x, y)$ between each node and its nearest cluster center is calculated, and a vector of nodes C is determined, containing the cluster numbers to which each node belongs. The coordinates of the cluster centers μ_k in each cluster are then recalculated by finding the average sum of the coordinates of the node vectors belonging to each cluster. A check is then carried out to see whether the coordinates of the current cluster centers have changed compared to the previous ones. If they have changed, the cycle is repeated to find new cluster center coordinates. If the coordinates have not changed, the cycle stops, and in each cluster the node closest to that cluster's center is identified and designated as the PCN.

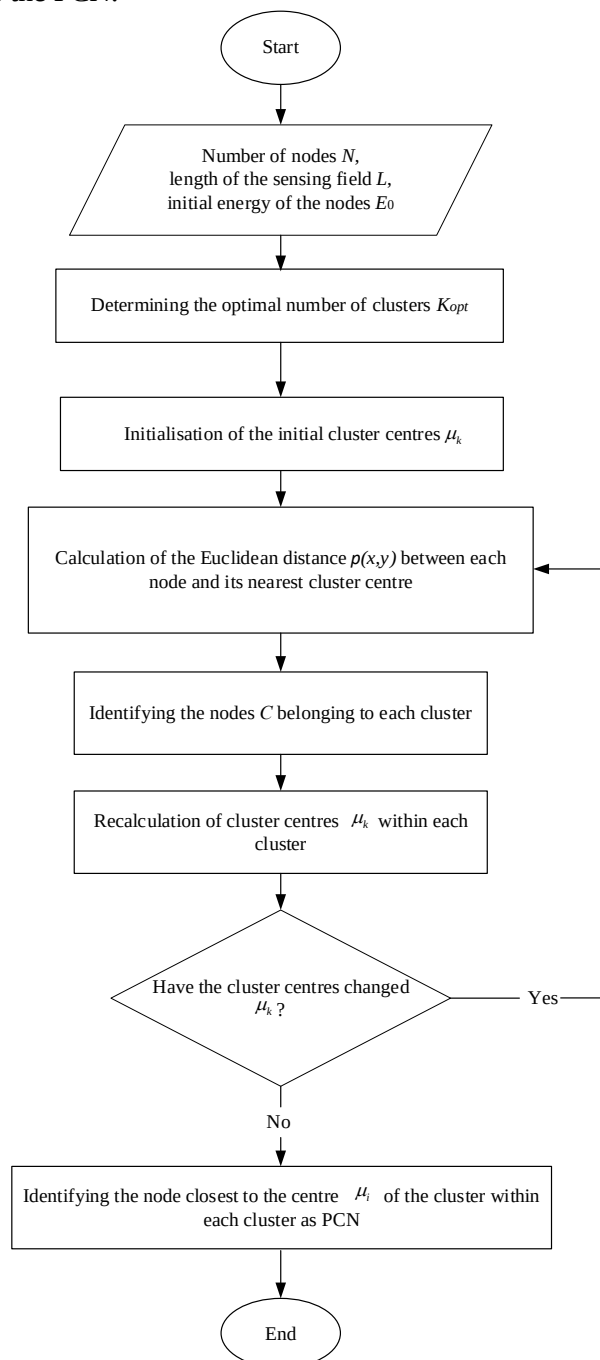


Fig. 3. Block diagram of the modified K-means algorithm

Source: compiled by the authors

As a result, an optimal sequence of clusters is formed in the sensor field and all principal cluster nodes are identified. The Hopfield neural network is used to construct the routing path via the obtained principal cluster nodes [7].

The Hopfield neural network model. The Hopfield neural network (HNN) is a single-layer recurrent network in which the neurons are fully connected, i.e. each neuron is connected to all other neurons. If there are two neurons i and j , then the connectivity weight between them is $w_{i,j}$, which is symmetric $w_{i,j} = w_{j,i}$. The Hopfield neural computing scheme [7], [9] is shown in Fig. 4.

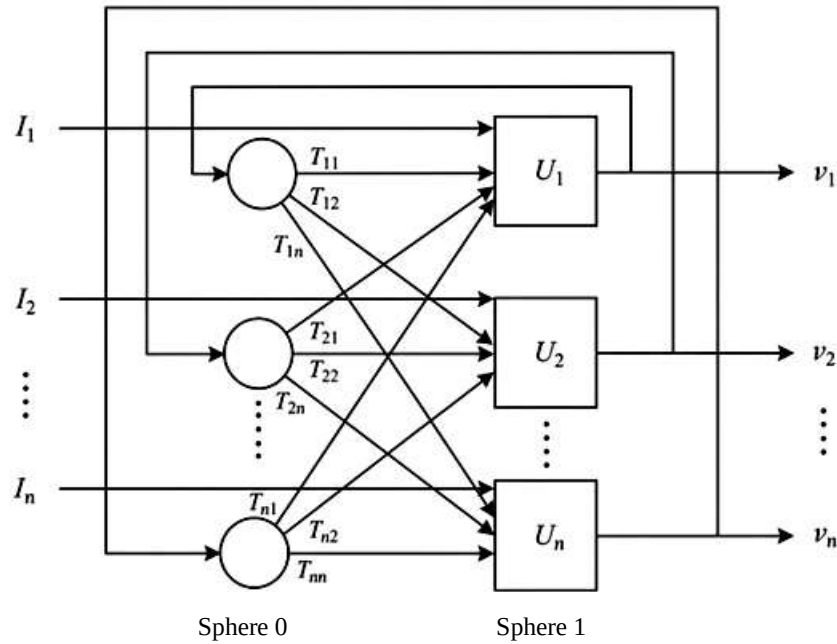


Fig. 4. Basic structure of a Hopfield neural network
Source compiled by the authors

Neurons are the processing elements. The output of each neuron is connected to the inputs of all other neurons via weights. Each connection in the communication network between two neighbouring nodes is associated with a single neuron. For example, the connection between node x and node i is associated with neuron. The output of neuron V_x , is determined by the input (x) and is evaluated using the sigmoid function (12). The input to each neuron is the sum of the outputs of other neurons y_j , weighted by the weights ($matrix T_{xi,yj}$), taking into account the external bias I_x . The parameter λ determines the convergence time and the correctness of the algorithm. For large values of λ , the logistic function becomes more step-like [7], [10].

$$V_{x,i} = g(U_{x,i}) = \frac{1}{1 + e^{-\lambda U_{x,i}}}, \quad (12)$$

$$\forall (x, i) \in \bar{N} \times \bar{N}, x \neq i,$$

where $V_{x,i}$ is the neuron's output; $U_{x,i}$ is the input to a neuron.

The aim of the HNN is to determine a directed path, represented as an ordered sequence of nodes, which connects the source node 's' to the destination node 'd', whilst ensuring that all links in the network have a non-negative cost ($C_{i,j}$). This path is called the ' ' and represents the minimum cost between the source and destination nodes. The cost matrix is usually symmetric ($C_{x,} = C_{i,x}$). The elements $C_{i,}$ are zero, since a node. cannot be connected to itself. The matrix ρx , (13) determines whether a connection xi exists in the network topology.

ρ_{xi} is defined as:

$$\rho_{x,i} = \begin{cases} 1, & \text{if the link } x_i \text{ does not exist} \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

The HNN converges when the change in each output value between consecutive iterations (ΔV_x) is below the threshold, i.e. $\Delta V_{th} < 10E - 5$. After this, a new matrix (Y_x) is estimated. If the output is greater than 0.5, Y_x is set to '1'; otherwise, is set to '0'. If $Y_x = 1$, then the link x_i is part of the shortest path; otherwise, it is not [7].

Furthermore, each neuron is externally stimulated by an input bias I_x (14), which incorporates the cost of connections and information about the network topology, as shown below:

$$I_{x,i} = -\frac{\mu_1}{2} * C_{x,i} * (1 - \delta_{x,d} \delta_{i,s}) - \frac{\mu_2}{2} * C_{x,i} * (1 - \delta_{x,d} * \delta_{i,s}) - \frac{\mu_4}{2} + \frac{\mu_5}{2} \delta_{x,d} * \delta_{i,s} \quad (14)$$

$$\forall (x \neq i)$$

$$\delta_{i,j} = \begin{cases} 0, & \text{if } i \neq j \\ 1, & \text{if } i = j \end{cases} \quad (15)$$

Where $I_{x,i}$ is the external shift, δ is the Kronecker function, and μ_1, μ_2, μ_4 and μ_5 are the HNN parameters. $\mu_{(1)}$ minimizes the total cost, μ_2 allows only links that exist in the path, μ_4 ensures convergence to a steady state, and μ_5 checks that the source and destination nodes are part of the path.

The matrix T , is defined as:

$$T_{xi,yj} = \mu_4 * \delta_{x,y} * \delta_{i,j} - \mu_3 * \delta_{x,y} - \mu_3 * \delta_{i,j} + \mu_3 * \delta_{j,x} + \mu_3 * \delta_{j,y} \quad (16)$$

$$\forall (x \neq i), \forall (y \neq j)$$

where T_{xi} , is connection or weight matrix; μ_3 is an HNN parameter used to ensure convergence.

Thus, if the system is Lyapunov-stable, the iterations lead to smaller changes in the output. Consequently, after a certain number of iterations, the HNN converges. Schuler et al. updated the neurons using equation (17). This equation made it possible to reduce the number of iterations required to achieve convergence and to minimize errors in pathfinding [7], [11].

$$U_{x,i}^{n+1} = U_{x,i}^n - A * U_{x,i}^{n-1} + B * \sum_{y=1}^n \sum_{j=1}^n T_{xi,yj} * V_{y,j}^n + C * I_{x,i} \quad (17)$$

where A, B and C are constants that configure the weights of the previous inputs.

The pseudocode for the HNN -based routing algorithm is shown below, in which U_{xi} is initialized with low and random values ($-0.0002 \leq U_{xi} \leq 0.0002$) to accelerate convergence.

Pseudocode for the Hopfield neural network [7]:

- obtaining parameters for constructing the weight matrix ($\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$);
- define the weight matrix ($T_{xi,yj}$);
- obtaining the parameters (source, destination, λ , A, B, C);
- obtaining the cost matrix ($C_{x,i}$);
- calculating the topological matrix and the displacement matrix ($p_{x,i}, I_{x,i}$);
- initialize the input neuron matrix ($U_{x,i}$);
- compute the output neuron matrix ($V_{x,i}$);
- while $\Delta V_{x,i} < \Delta V_{th}$ do;
- calculation of the new matrix of input neurons ($U_{x,i}$) using (17);
- calculation of the output neuron matrix ($V_{x,i}$) using (12);
- applying a threshold function to the matrix of output neurons (Y_{xi});
- determining the route from Y_{xi} .

Data collection and routing protocol. A protocol has been developed for a terrestrial wireless sensor network that combines clustering, data collection and shortest path finding via all

KmHNNSP (K-means and Hopfield Neural Network for Shortest Path) clusters between cluster nodes for data transmission to a terrestrial gateway. This protocol is based on the integration of a modified K-means algorithm for clustering the NWSN and identifying PCN, and the Hopfield neural network algorithm for finding a data transmission path between PCN to the ground-based gateway.

Fig. 5 illustrates the operating principle of the KmHNNSP protocol, which consists of two stages:

1) *The cluster formation stage* – which includes:

- selection of the optimal number of clusters using formula (10);
- cluster formation using a modified K-means algorithm;

2) *The data transmission stage* – each round of data transmission involves:

- selection of PCN within the formed clusters and subsequent periodic transmission of the PCN status in each cluster in accordance with the following formula to extend the network's lifetime:

$$y_{PCN} = r \bmod n,$$

where n is the number of nodes in the cluster; r is the round number; y_{PCN} is the node that will be selected as the PCN.

- Intra-cluster data transmission: sending data from nodes and collecting it at PCN.
- Selection of the shortest path passing through all PCN using a Hopfield neural network,
- Inter-cluster data transmission: data is transmitted from PCN to a ground gateway. In each round of data transmission/reception, the energy consumption of each node is calculated.

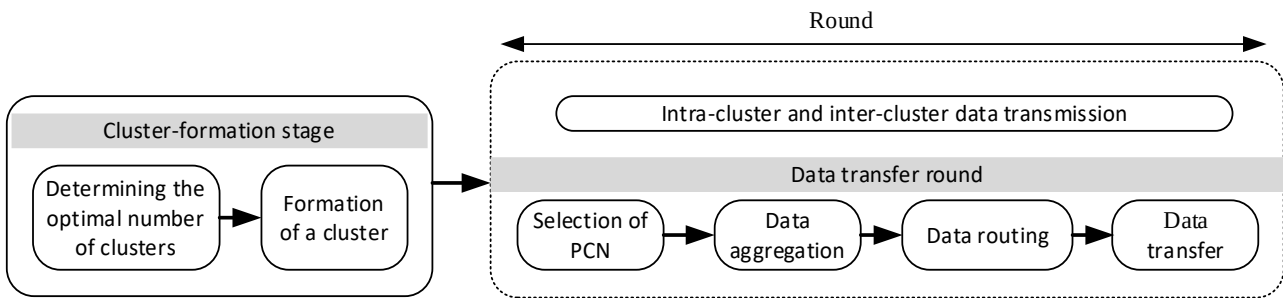


Fig. 5. Diagram of the stages of the *KmHNNSP* routing algorithm

Source: compiled by the authors

Block diagram of the NWSN clustering and routing algorithm for the *KmHNNSP* protocol is shown in Fig. 6.

The diagram illustrates the formation of clusters using a modified K-means algorithm, and the check in each round to determine whether all nodes are dead. If all nodes are dead, the protocol terminates; if there are live nodes, then PCN are selected for each cluster, a path between these PCN is determined, and data transmission begins first within the cluster, then between clusters, and finally to the base station. During each data transmission and reception, only those nodes that are sending data consume energy in accordance with the node life cycle flowchart, whilst dormant nodes do not send data and do not consume energy. At the end of a round, a survey of the nodes is carried out; dead nodes are removed from the clusters, after which the next round begins, and so on.

Dijkstra's algorithm. After data collection in the ground segment of a heterogeneous UAV network, the aggregated data packet is transmitted from the ground gateway to the base station via a swarm of UAVs, which requires a routing problem to be solved. This is one of the key tasks in UAV networks, involving the search for the shortest path for data transmission from the source to the receiver. In this study, Dijkstra's algorithm was used as a test case; it constructs a shortest-path tree starting from the source based on two groups: the first group contains vertices in the shortest-path tree, whilst the second group contains vertices that have not yet been added to the shortest-

path tree. Whilst the algorithm is running, we search for a vertex in the set of vertices not yet added to the tree that has the shortest possible distance from the source.

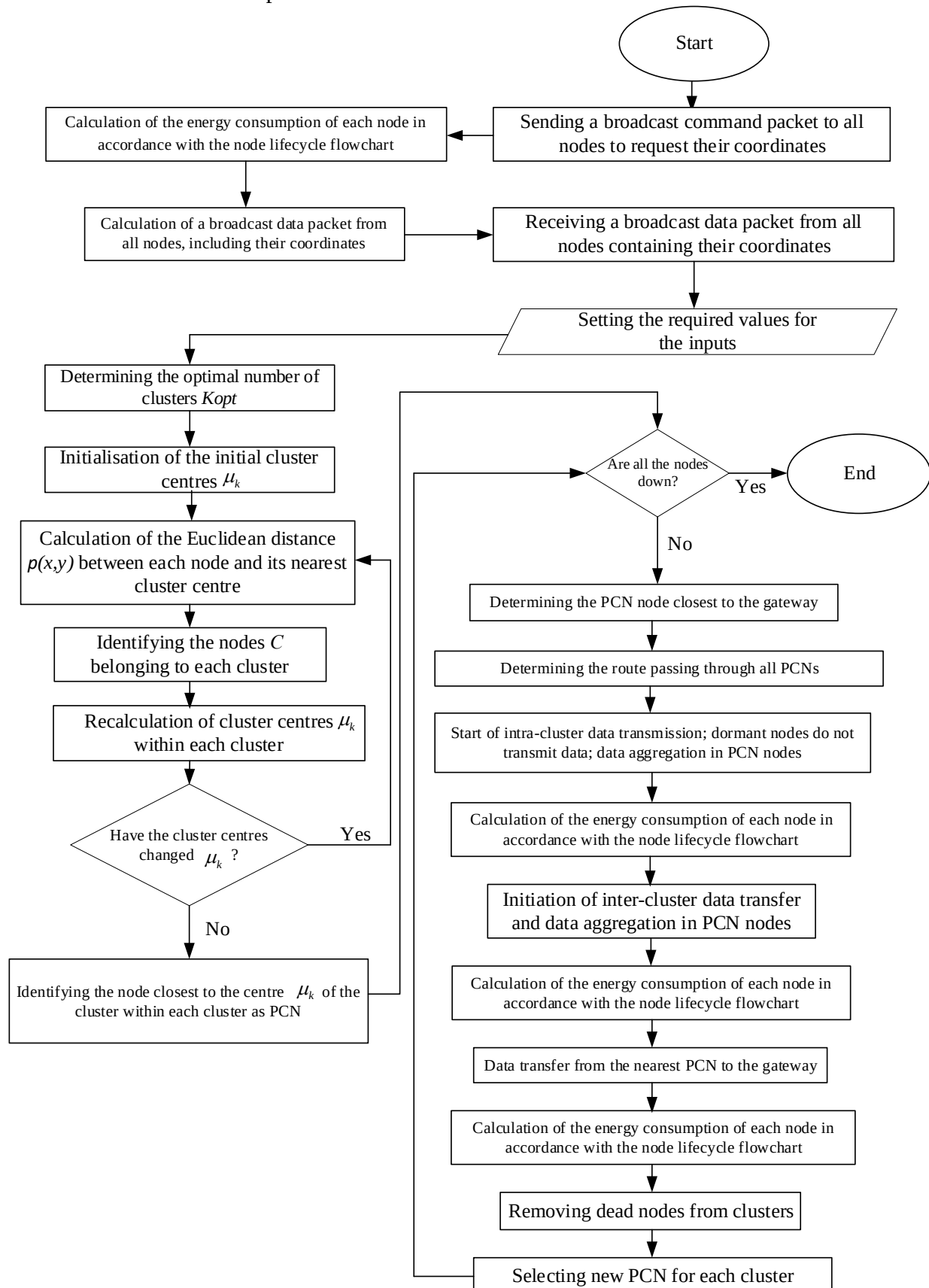


Fig. 6. Block diagram of the NWSN clustering and routing algorithm

Source: compiled by the authors

The simulation model developed utilizes a number of constraints, described below in the proposed shortest-path search algorithm. The following assumptions and constraints were made in the simulation modelling:

- UAVs in the model are treated as points with specified coordinates that change over time;
- the situation is considered at a fixed point in time;
- the points (UAVs) are approximately uniformly distributed within a three-dimensional model cube, with relative coordinates x, y, z (0, 0, 0), (1, 1, 1) in the layer between the planes $z=0.7$ and $z=1$;
- the signal source from the network of ground-based sensors is located near the point (0, 0, 0) – the origin. This is a model of a signal receiver from the network of ground-based sensors;
- the base station or server to which the signal is to be transmitted is located near point (1,1,0);
- at a given point in time, the UAV swarm is clustered using the K-means method;
- the clusters in which the UAVs are located closest to the signal source from the network of ground-based sensors (UAV_1) and to the base station (UAV_2) are then identified.

The signal is transmitted from the receiver to UCP_1, then the Dijkstra algorithm is activated to find the shortest path between UCP_1 and UCP_2, and the signal from UCP_2 is transmitted to the base station.

Discussion and limitations. A study was conducted of two clustering algorithms for a ground-based wireless sensor network with varying numbers of sensors: the Kohonen network training algorithm using the Constructive Method and the modified K-means algorithm. It was found that the Kohonen neural network with the Constructive Method is unable to determine the optimal number of clusters, whilst the modified K-means algorithm allows the optimal number of clusters to be found; consequently, the modified K-means algorithm was selected for the software package. The investigation and modelling of data routing in a swarm of UAVs using Dijkstra's algorithm and a genetic algorithm showed that the genetic algorithm enables the shortest path between UAVs to be found in a fraction of a second whilst the network topology is dynamically changing, whereas Dijkstra's algorithm does not take into account data from the radio visibility matrix;

Conclusions. This paper presents an algorithm that combines the Kohonen network construction method with the Constructive Method for clustering a ground-based wireless sensor network;

A method has been developed for the efficient clustering of a ground-based wireless sensor network using a modified K-means algorithm, which employs an analytical method to determine the optimal number of clusters for a given number of nodes distributed across the sensing area. The modified K-means algorithm enables the optimisation of the number of clusters and avoid the 'congestion' of UAVs in a small area of the coverage zone, thereby reducing the time required for information processing at the ground gateway; for the aerial segment of a heterogeneous UAV network, based on UAV location data, Dijkstra's algorithm was tested, which enables the shortest route within the swarm to be found. This method enables data to be transmitted from the ground gateway to the base station for processing.

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Застосування методів інтелектуального аналізу даних для обробки трафіку в бездротовій сенсорній мережі

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АНОТАЦІЯ

Бездротові сенсорні мережі (БСМ) дають змогу збирати та передавати дані в Інтернеті речей (IoT – Internet of Things), при цьому, вони широко використовуються в різних галузях, таких як військова, промислова, сільськогосподарська, екологічна, транспортна, соціальна та медична. Бездротові сенсорні мережі належать до мереж, що забезпечують безперервний зв'язок та доступ до інформації в будь-який час і в будь-якому місці. Основні напрямки досліджень в роботі пов'язані із застосуванням методів інтелектуального аналізу даних з метою поліпшення характеристик передачі даних та показників якості в гетерогенній бездротовій сенсорній мережі, яка складається з наземного сегменту зі стаціонарними сенсорними вузлами та літаючою мережею, що є вкрай актуальним завданням під час моніторингу та контролю зон покриття з використанням Інтернету речей. В роботі досліджено метод ефективної кластеризації в наземній бездротовій сенсорній мережі, який забезпечує визначення та розподіл оптимальної кількості кластерів і позначення головних кластерних вузлів, що, в результаті, забезпечує ефективну обробку та передачу трафіку в різних сегментах мережі. Запропоновано і продовжують розроблятися підходи, що об'єднують різні способи побудови кластерів і передачі даних між вузлами різних топологічних типів. Дані можуть бути відправлені з кінцевого вузла безпосередньо на базову станцію або через головний кластерний вузол, або через їх послідовність, перш ніж потрапити на базову станцію. При вирішенні поставлених завдань використовувалися методи теорії графів, штучних нейронних мереж, генетичного алгоритму та К-середніх, а також інженерії програмного забезпечення.

Ключові слова: алгоритм; аналіз даних; штучний інтелект; Інтернет речей; метод; кластерний вузол; кластеризація; трафік; нейронна мережа; бездротова сенсорна мережа; інженерії програмного забезпечення

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