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Research Article

MR-Pareto: A Multiattribute Opportunistic Routing Method Based on Pareto Optimal Solution for Mobile Crowdsensing

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Mobile crowdsensing (MCS) is a new perception mode for solving large-scale mobile sensing tasks. Traditional data transmission methods are inapplicable, as the MCS is affected by coverage, user preference, and network access cost. Opportunistic network data transmission schemes in MCS have recently witnessed a surge of research efforts due to their ability of high delivery and low consumption. However, existing works only focus on the impact of the geographical location of nodes on user needs or the interaction between social information and data, which do not take into account the temporal and spatial characteristics of nodes. To address these issues, this paper proposes a multiattribute routing method based on Pareto optimal (MR-Pareto) solution to construct a balance between the energy consumption and resource constraints of nodes in transmission protocols. First, the attribute relationship between nodes is analyzed, which was aimed at selecting the nodes within a contact time threshold. Then, based on a nondominated sorting approach, we achieve a Pareto optimal set of candidate nodes. Finally, the relay nodes for forwarding messages are determined by comparing the cache size and the remaining energy. The experimental results demonstrate that our proposed method has low network overhead, low packet loss, and high message delivery rate, compared to epidemic and prophet routing strategies.

1. Introduction

With the development of pervasive computing, mobile crowdsensing technology, and intelligent terminal devices, intelligent systems with integrated sensing and computing communication capabilities have been widely deployed. MCS migrates perception tasks from a centralized platform to a distributed computing terminal across the space-time dimension, which can not only achieve data analysis and understanding but also make large-scale and high-precision environment perception possible [1, 2]. Nowadays, MCS has attracted great attentions from various research institutions [3].

In traditional data transmission methods, it is difficult to satisfy the actual needs of data acquisition by only using pre-deployed dense sensor nodes in an uncertain and large-scale sensing environment, such as limited network resources and heterogeneous sensing terminals. MCS can use ubiquitous intelligent terminals and networks (i.e., WiFi, 4G, and 5G) cooperatively to improve the sensing quality, which is especially suitable for the environments with low network coverage or expensive access network (e.g., remote areas, large cities, and disaster recovery). The performance of MCS routing method plays an important role in sensing the task transmission quality. MCS has the characteristics of sparse node distribution, intermittent connection, and dynamic topology change, which is similar to the opportunistic routing. Therefore, data forwarding through opportunistic routing transmission mode can leverage the advantages of MCS [4]. The advantages are as follows: (1) opportunistic routing method can reduce the cost of network deployment, make full use of millions of mobile devices to build large-scale sensing networks, and ensure the privacy of user data. (2) It does not need any centralized servers or infrastructures for communication and management. Through the opportunity contact between mobile users, the mode of "store-carry-

forward" [5] is adopted to transmit the sensing data, which can reduce the workload of cellular network in dense areas and make the maintenance of network easier.

Up to now, the research on MCS opportunistic routing methods has mainly focused on the following aspects: (1) node location, which influences the impact of user demand; (2) data interaction, which determines how to select a suitable set of users; (3) balance between node energy and cache. Although the aforementioned aspects will affect the routing transmission performance of the MCS, the routing algorithm that comprehensively considers them is rare.

There are aspects that have an impact on the routing transmission performance of MCS. However, it is rare to consider all three aspects together.

Under the environment of weak network and limited resources, we propose a multiattribute opportunistic routing method for MCS that can achieve efficient node transmission by selecting the appropriate relay nodes and node local resource information (i.e., node motion state, node history connection, node energy, and capacity) and reducing network energy consumption and overhead. We considered energy consumption, cache level, and internode relationship as combined parameters in the routing process, instead of considering them separately as in literature [6, 7]. In addition, we added spatiotemporal characteristics to further constrain the nodes' forwarding decisions.

Our major contributions can be summarized as follows.

(1) We proposed a multiattribute routing method based on Pareto optimal (MR-Pareto) and evaluated the stability of node connection based on the user motion state. The energy and cache attributes of user terminals are introduced to improve the data delivery rate and reduce the communication load

(2) By analyzing the impact of different indices on candidate nodes in MCS, we noticed that the optimal candidate nodes are related to node centrality, correlation, and similarity. Through these three indices, we achieved the Pareto optimal result by using nondominated sorting

(3) Acceptance rates have historically run at slightly over 50%. There is no sufficient room within the technical program to accept all submissions

The rest of the paper is organized as follows: Section 2 discusses the related work. Section 3 introduces the detection of node location in the network. The opportunistic routing method based on Pareto optimal solution is presented in Section 4. In Section 5, we evaluate our proposed method and present evaluation results. Finally, we conclude this paper in Section 6.

2. Related Work

In the last decade, many opportunistic routing schemes have been designed to facilitate process of data routing. Generally, opportunistic routing schemes can be classified into geographic schemes, link state aware schemes, and probability schemes. The first category covers schemes based on locations. The second category covers schemes that take link states and nodes' energy into account. In the third category, probability is used to tackle the problems of node mobility.

Geographic opportunistic routing can overcome the issue of lack of infrastructure due to the dynamic property of MCS. A number of geographic metrics have been studied [8]. For instance, LIPS is a geographic scheme where the complication caused by the multiturning point structure can be overcame by the virtual plane mirror algorithm [9]. To handle asymmetric links, FQ-AGO [10] utilizes a fuzzy logic approach and employs the Q-learning algorithm to select the most stable link. MGOR uses a multiple channel to improve routing efficiency and take opportunistic effective one-hop throughput as a new local metric to solve the impacts of multiple rates, as well as candidate selection, prioritization, and coordination. To reduce energy cost of multipath routing approach, EQGOR [11] selects and prioritizes the forwarding candidate set in an efficient manner, which is suitable for WSNs in respect of energy efficiency, latency, and time complexity.

Opportunistic routing improves the reliability of packet delivery by broadcasting of the wireless link. Choosing the next relay at each hop based on the link state, opportunistic routing guarantees the packet delivery ratio. In [12], Li et al. propose the probability prediction-based reliable and efficient opportunistic routing (PRO) algorithm. Based on PRO, the variation of signal-to-interference-plus-noise ratio (SINR) and packet queue length (PQL) of the receiver can be predicted. In [13], Zhang et al. propose a link availability probability prediction model and a new concept called the link correlation which is used to represent the influence of different link combinations. Based on these conclusions, a street-centric opportunistic routing protocol which is based on the expected transmission cost over a multihop path is proposed. Wu and Ma [14] formulate a rate distortion model to represent the fact that the immoderate utilization of wireless fading channels could incur high distortion due to high probabilities of video package loss and damage. Based on the model, the authors propose the routing algorithm to seek a balance between the distortion and delay.

Since it is hard to decide whether an encountered node is a good relay at the moment of encounter, choosing the relay nodes based on the probability is a feasible solution. In [13], Zhang et al. propose a link model by Wiener process to represent the influence of different link combinations in network topology. Based on the model, the authors design an opportunistic routing metric called the expected transmission cost over a multihop path. To dynamically determine relay candidate set and take into account the effects of uncertainty in node wake-up times, Zhang et al. [15] propose an opportunistic routing which constructs candidate set based on the relatively stable topology and duty-cycle length information.

Most of the existing studies only forces on one attribute, such as the geographic location or the probability. In order to improve network performance in mobile crowdsensing networks, it is necessary to comprehensively consider the influence of spatiotemporal correlation between perception

nodes on network performance and evaluate the importance of each attribute by objective weight when judging each indicator. Therefore, this paper takes the relationship between nodes as the main evaluation index, fuses the nodes' motion state in space, and proposes a method named multiattribute routing based on Pareto optimal (MR-Pareto), which uses the nondominant ordering of objective weighted evaluation method based on focusing on the energy of nodes and cache.

3. Node Position Detection

Since the nodes are mobile, the network links are prone to be interrupted. Therefore, based on the sharing of geographical location information, the nodes that can successfully forward messages within the time threshold are screened out in this paper. Each node periodically broadcasts Hello information within a hop range. When the node i receives the Hello packet sent by the node j or the location information that the node broadcasts, the node i can determine the encounter with the node j. This information contains the geographical position, movement speed, and direction at the current time. With the help of the publishing mechanism of geographical location information, the region of the neighbor node within the range of the forwarding node can be determined, and the node can scan the updated neighbor list within a certain period to detect the future geographic location of the neighbor nodes combined with the saved location coordinate information. (x_i, y_i) is defined as the position coordinates of node i, and (x_i, y_i) is defined as the position coordinates of node j, and then, the distance between two communication nodes $\text{Dist}(i, j)$ can be calculated by formula (1):

$$\text{Dist}(i, j) = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}. \quad (1)$$

Figure 1 is the schematic diagram of the neighbor nodes in the detection communication range waiting for the message to be forwarded. Suppose $\text{Range}(i)$ is the communication range of node i, $\text{Dist}_{\text{now}}(i, j)$ is the current distance between node i and node j, and $\text{Dist}_{\text{pro}}(i, j)$ is the sine component of the velocity vector difference between node i and node j when the node j reaches the boundary of the communication range of node i. $\text{Dist}_{\text{rest}}(i, j)$ means the remaining distance of sustainable connection between the two nodes within the communication range, which can be calculated as follows:

$$\text{Dist}_{\text{rest}}(i, j) = \sqrt{\text{Range}^2(i) - \text{Dist}_{\text{pro}}^2(i, j)} - \text{Dist}_{\text{now}}(i, j) \cdot \cos \theta_0. \quad (2)$$

To prevent link interruption caused by node movement, it is necessary to detect whether the location of neighboring nodes around the forwarding node is still within the reachable communication range after exceeding the transmission time threshold $T_{\text{threshold}}(i, j)$. If the node can ensure that the link is always connected during the process of forward-
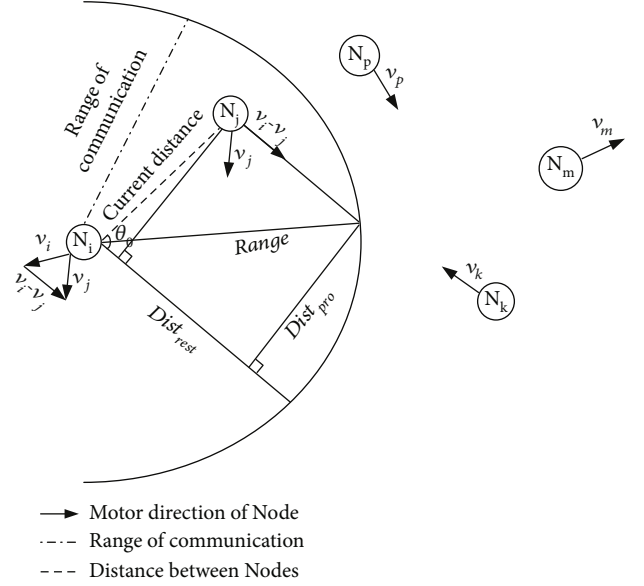

FIGURE 1: The node probes the neighbor nodes.

ing all the different messages to the neighbor nodes, it can be confirmed that this node meets the requirements of location transmission.

By comparing the relationship between the transmission time threshold of link continuous connection and the remaining connection time during message forwarding between two nodes, we can determine whether the forwarding requirements are met. $T_{\text{threshold}}(i, j)$ is determined by the length of node exchange message, and the remaining connection time $T_{\text{rest}}(i, j)$ between node i and node j can be calculated in equation (3):

$$T_{\text{rest}}(i, j) = \frac{\text{Dist}_{\text{rest}}(i, j)}{\left|v_i - v_j\right|}. \quad (3)$$

4. A Multiattribute Routing Method Based on Pareto Optimality

4.1. Pareto Candidate Node Set. Due to the lack of fixed infrastructure and the constantly changing network topology in mobile group-intelligence perceptions, each node needs to meet its neighbor nodes to carry out data transmission. Since the communications between nodes are influenced by trajectory and behavior factors, it is typical to choose a reliable and utility node transmission task when choosing relay nodes. Two node contact should be relatively stable and frequent, so that the transmission of sensory data can be accomplished in order to better use collaboration between the nodes to adapt to the change in the network structure. Therefore, the centrality, similarity, and relevance of nodes are taken as the basis for the selection of relay nodes in this paper.

Definition 1. Node centrality.
The number of current neighboring nodes is commonly taken as the criterion to measure the centrality of nodes. [16]
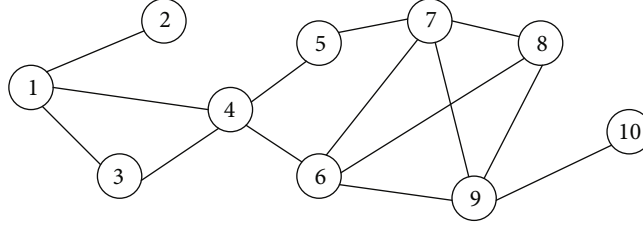
Figure 2: Small-scale mobile crowdsensing network.

showed that according to the data generated by multiarea mobile devices, after comparison and analysis, nodes form certain connection relationships after multiple contacts, which facilitates the understanding of social behaviors of potential users in wireless networks and leads to information diffusion. The more centrality a node has in the MCS network, the more it can promote network communication. Centrality is usually represented by the degree of a node in an undirected graph. In an undirected graph with nodes, the centrality of the node is defined as

$$\mathrm{CEN}(i) = \sum_{j=1}^{n} A_{ij}(i \neq j), \tag{4}$$

where $\mathrm{CEN}(i)$ represents the center degree of the node i and is also the sum of nodes that can be contacted by the node i and other $n - 1$ nodes in the network and A represents the adjacency matrix of node i and node j contact. It is assumed that the contact of nodes is bidirectional. If there is a path from node to node, there is also a path from node i to node j. A is the symmetric matrix of n by n. If there are edges between node i and node j, we have $A_{ij} = 1$; otherwise, $A_{ij} = 1$. Therefore, the node center degree can be calculated by formula (4). It can not only reflect the relationship between the node and other nodes but also reflect the key degree of this node according to the network scale. As shown in Figure 2, a mobile crowdsensing network with a number of 10 nodes can be obtained. According to the above definition, the centrality of node 4 is 4.

Definition 2. Node correlation.

Node correlation is used to represent the probability of meeting nodes that can transmit messages through collaboration in mobile crowdsensing network. When the probability of confrontation between the node and the destination node is higher, the ability of the node to forward to the destination node is stronger, and the delivery rate of messages in MCS network is higher. The duration of connection establishment and the time interval from the last mutual contact represent the time and frequency of each node's contact with other nodes.

Assuming that the contact time follows an exponential distribution, it represents the probability of the duration of two nodes in a certain period of time [17]. The node correlation is shown in equation (5):

$$\mathrm{COR}(i, j) = 1 - \exp\left(-\frac{U(i, j)}{I(i, j)}\right). \tag{5}$$

where $\mathrm{COR}(i, j)$ represents the probability of the node i and the node j meeting within a period of time, $U(i, j)$ is the length of the last connection between the node i and the node j, and $I(i, j)$ is the time interval between the node i and the node j from last connection. The longer the connect time of duration (the connection time) between nodes, the higher the value of $COR(i, j)$; the shorter the interval from the last connection, the higher the value of $COR(i, j)$. If the node i and the node j experience a long period of time since the last encounter, the probability of meeting is updated by the decay factor γ within the time t from the last encounter, as shown in equation (6). If two nodes can meet again after a short contact, and the span of the two encounters is shorter, the possibility of the two nodes meeting again in the future is greater.

$$\mathrm{COR}(i, j) = 1 - \mathrm{COR}(i, j)_{\mathrm{old}} \times \gamma^{t}. \tag{6}$$

Definition 3. Node similarity.

Two nodes are more similar if they have several common neighboring nodes and they often meet. $N(i)$ and $N(j)$ are defined as the set of neighbor nodes of nodes i and j, respectively. $S(i, j)$ can be measured by

$$S(i, j) = N(i) \cap N(j). \tag{7}$$

Since each node i cannot obtain global information, the similarity of all common neighbors is estimated by exchanging $N(i)$ with $N(j)$ and when $N(i)$ satisfied $N(j)$. Newman [18] calculated and verified the relationship between the number of common neighbors at time t and the probability of their future cooperation. The similarity of the node i and the node j in MCS network is represented by the ratio of the intersection set of all common neighbor nodes existing between other nodes encountered by these two nodes and the union set of their respective neighbor nodes, and the similarity $SU(i, j)$ is shown in equation (8).

$$\mathrm{SU}(i, j) = \left| \frac{N(i) \cap N(j)}{N(i) \cup N(j)} \right|. \tag{8}$$

If the intersection number of neighbor nodes set of the two nodes is larger, it can be seen that the two nodes are more likely to forward messages through the common relay node. Therefore, the calculation of similarity can reflect the

efficiency of message transmission to a certain extent. When calculating the similarity process between two nodes, the symmetric matrix can be expressed as the similarity between nodes in MCS network by referring to the graph theory of node centrality. In Figure 2, according to the above definition, it can be determined that the similarity of node 4 and node 7 is 1/3, and their common neighbor nodes are node 5 and node 6.

4.2. Nondominated Sorting. Since the centrality, relevance, and similarity of nodes are taken as comprehensive evaluation indexes in this paper, in order to make these three attributes reflect the overall characteristics of the relationship between nodes, it is necessary to select the comprehensive evaluation method of multiple factors to calculate the weight of each attribute element, so as to maximize the characteristic values of the relationship between nodes. According to the comprehensive evaluation of multiple factors, it can be classified as subjective weighting evaluation method and objective weighting evaluation method [19]. The subjective weighting evaluation method takes the attention level of the strategic decision-maker in each evaluation indicator as the standard and determines the weight distribution of multiple indicators by subjective assumption. Because the raw data in this method follow the subjective judgment of experience and human factors interfere greatly, it has obvious limitations in the comprehensive evaluation of the three attributes representing the relationship between nodes in MCS network. Therefore, this paper adopts the nondominant ordering method in the objective weighted evaluation method, which can solve the problem of how to obtain the optimal solution by combining the objective functions constructed by the three attributes when the three objective functions of node centrality, relevance, and similarity are in conflict. However, this kind of problem can only seek the noninferior solution; that is, Pareto is optimal. Therefore, the quantization problem of the relationship between the attributes of three nodes is transformed into the problem of comparing the overall characteristics between nodes.

Definition 4. Pareto dominance.

For multiple objective function minimization problems, assumption of a vector is $\bar{f}(\bar{X}) = (f_1(\bar{X}), f_2(\bar{X}), \cdots, f_n(\bar{X}))$, which is made up of n target components $f_i(i = 1, 2, \cdots, n)$, given any two decision variables $\bar{X}_u, \bar{X}_v \in U$: If and only if, for $\forall i \in \{1, 2, \cdots, n\}$, there is $f_i(\bar{X}_u) \leq f_i(\bar{X}_v)$ and there is at least one $j \in \{1, 2, \cdots, n\}$. Make $f_j(\bar{X}_u) \leq f_j(\bar{X}_v)$ true; thus, $\bar{X}_u$ has weak-dominated of $\bar{X}_v$. If and only if, $\exists i \in \{1, 2, \cdots, n\}$, then $f_i(\bar{X}_u) < f_i(\bar{X}_v)$; at the same time, $\exists j \in \{1, 2, \cdots, n\}$. Make $f_j(\bar{X}_u) > f_j(\bar{X}_v)$ true; thus, $\bar{X}_u$ non-dominates $\bar{X}_v$.

The proposal of nondominated sorting method is to solve the Pareto optimal solution set [20]; the method is based on the Pareto solutions of individuals to hierarchical groups, aiming the algorithm used the cycle to adapt to the grading at the mercy of the form, the search direction to the Pareto optimal solution set to calculate the final result.

If there is only one objective function, the maximum or minimum solution is in the limit position in the global, so it is better than other solutions in the solution set. If the problem consists of multiple objective function, multiple function cannot be achieved in the process of solving the absolute equilibrium state. It is difficult to find a solution to make the multiple objective function to achieve the best effect; in other words, even though a solution can ensure that the result of the objective function is optimal, the rest of the function is not necessarily the best result. Therefore, for multiobjective optimization problems, there is often a set, which cannot be compared between all objective functions and their characteristics; that is, the utility of an objective function cannot be reduced without increasing the utility of any objective function. This solution called nondominated solution or Pareto optimal solution is defined as follows:

For multiobjective minimization problems, assumption of a vector is $\bar{f}(\bar{X}) = (f_1(\bar{X}), f_2(\bar{X}), \cdots, f_n(\bar{X}))$, which is made up of n target components $f_1(i = 1, 2, \cdots, n)$. Set $\bar{X}_u \in U$ is the decision variable; if $\bar{X}_u$ is Pareto's optimal solution and then if and only if, when the decision variable $v = f(\bar{X}_v) = (v_1, \cdots v_n)$ cannot dominate $u = f(\bar{X}_u) = (u_1, \cdots u_n)$, $\bar{X}_v \in U$, do not make formula (9):

$$\forall i \in \{1, 2, \cdots, n\}, v_i \leq u_i \cap \exists i \in \{1, 2, \cdots, n\} | v_i \leq u_i. \quad (9)$$

To find the Pareto optimal set means to find the Pareto optimal front. As shown in Figure 3, the points on the line represent viable choices, where smaller values are better than larger ones. Point C is not at the Pareto boundary because it is controlled by points A and B. Points A and B are not strictly occupied by any other points, so they do lie on the boundary.

When a node performs a fast nondominant ordering of its neighbor nodes, the population size is assumed to be P, and two parameters n_p and S_p of each individual p in P need to be calculated in this algorithm. n_p in the population represents the number of individuals of dominant individual p, which is determined by the first nondominant layer of the number of individuals in the feasible solution set that can be dominated and is expressed as the set of individuals that are dominated by individual p, and its quantitative determination is based on the result that all individuals in the feasible solution can be dominated by individual p constituting the set. After traversing the entire population, the complexity of the algorithm is $O(mN^2)$ [21]. The main steps of the algorithm are as follows:

(1) Identify each $n_p = 0$ individual in the population and store it in the current nondominant set F_1

(2) Consider of all the individual i in the present constituted set of nondominating and then look at the set of individuals S_i which they can dominate; if there exists an individual l in S_i, then reduce the dominated set of individual L by 1, namely, $n_l = n_l - 1$ (due to the fact that the elements which the individual l can control in the governing set S_i are already
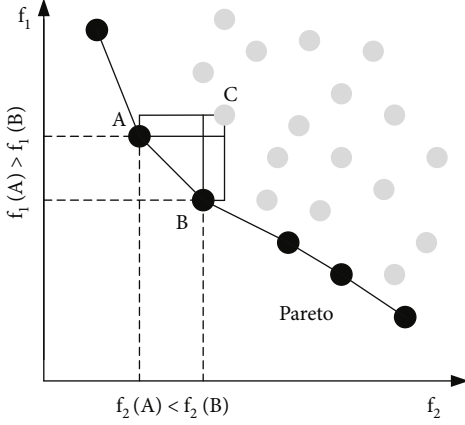
FIGURE 3: Pareto frontier.

stored in S_i); if n_l reduces to zero, namely, when $n_l = 0$, store the individual l into other set H

(3) Consider the first nondominant solution set as the entire solution set which represents the optimal set of individuals, since only the disposable individuals can be constrained by any other individuals in the set, for each individual in the set based on a similar nondominant order. Then, the hierarchy of the set is defined by the above steps, and the same nondominant order is given until each individual in the set is graded

The selection of Pareto candidate node set refers to the Pareto optimal solution set obtained by the social context information results between nodes, taking the three attributes of centrality, relevance, and similarity as objective functions and computing the objective weighting evaluation method of nondominant ordering. Not only does this algorithm take into account the local connections between nodes but also avoids the interference of subjective factors on the determination of weights, as shown in Algorithm 1.

4.3. Relay Node Determination. In mobile crowdsensing system, users usually use small smart mobile terminals as perception devices. Although these devices have considerable computing power and perception capacity, they often have certain limitations in energy or cache reserve. If the power or cache of the device cannot meet the work needs, the perception task undertaken by the device will not be completed, and the performance of the whole network will be greatly reduced [22].

Due to node energy consumption, which is mainly caused by the data transmission task processing, signal processing and hardware operation [23], data transmission, and the task process, the energy consumption is larger. Therefore, the model is established based on the energy which mainly considers two aspects of data transmission and task processing and data transmission energy consumption including node scanning, sending messages, and receiving messages, three parts. The energy consumption of node scanning is defined as the energy consumed when the node

```
1:  Input: Node Set P
2:  Output: Candidate Node SetPareto
3:  Procedure ParetoCandidate
4:  Calculate the centrality of node
       CEN(i) = Σⁿⱼ₌₁ Aᵢⱼ(i ≠ j)
5:  Calculate the correlation of node
       CORᵢⱼ = 1 − COR(i, j)ₒₗ𝒹 × γᵗ
6:  Calculate the similarity utility of node
       SUᵢⱼ = |N(i) ∩ N(j)/N(i) ∪ N(j)|
7:  LET F be the first dominating set
       % Non-dominated Sorting
8:  for p in P do
9:    let Sp be the dominating set
10:     for q in Pdo
11:         add q to the Sp list when p dominates q
            nₚ add 1 when p is dominated by q
            take nₚ of the individual is 0 be F1
12:     end for
13: end for
14: F.append(F₁)
15: SET index = 0
16: while F [index] do
17:   let Q be the dominated individual set
            Sort Sp
            F.append(Q)
            index ⟵ index + 1
18: end while
```

ALGORITHM 1: Select nodes from candidate node set Pareto.

carries out periodic scanning of the surrounding environment, including the energy consumption when scanning the node channel preparing for communication and sensing data. Let e_s be the energy lost in a single scan of the node, t be the working time of the node and be the scan cycle, and then, the energy consumption of node scan E_s can be defined as formula (10):

$$E_s = e_s \times \frac{t}{T}. \tag{10}$$

When a node transmits data, the data length is usually used to measure the amount of energy consumed. Therefore, the energy consumption during message sending and receiving is set as a positive correlation function with the corresponding message size. When the message size is larger, the energy consumption during transmission is larger. Let e_t, e_r, and M_{size} denote the energy required to send a unit message, the energy required to receive a unit message, and the message size, respectively. Energy consumption for sending messages is given by

$$E_t = e_t \times M_{size}, \tag{11}$$

and energy consumption for receiving messages is given by

$$E_r = e_r \times M_{size}. \tag{12}$$

Since task processing represents mostly the energy consumed by tasks running in the background of user nodes, the use of cache space is taken as the measurement factor of energy consumption required by node tasks. If the cache space used by nodes is large, it indicates that there are more tasks running in the background, thus consuming more energy. Let e_d denote the energy consumption per unit message processing and B denote the use size of cache space. We can compute the task processing energy consumption by

$$E_d = e_d \times B. \tag{13}$$

Let E, $E_{consume}$, and $E_{current}$ denote the total energy value of the node, the energy consumed by the node, and the residual energy of the node, respectively. $E_{consume}$ and $E_{current}$ can be computed by

$$\begin{aligned} E_{consume} &= E_s + E_t + E_r + E_d, \\ E_{current} &= E - E_{consume}. \end{aligned} \tag{14}$$

In order to deal with the problem of excessive depletion of node resources in mobile crowdsensing network, this algorithm takes full account of the dynamic changes of residual energy of nodes and cache space when selecting relay nodes and defines the measurement value of relay nodes as shown in formula (15)

$$EB = \alpha E_{current} + \beta B, \tag{15}$$

where α and β denote the tuning parameter. When the measure value of the node EB is greater than the average value of the measure value of all nodes in the Pareto candidate node set, this node is regarded as a relay node.

4.4. Message Forwarding Strategy. In the message forwarding phase, nodes detect all neighbor nodes, according to the update location information table and the neighbor table. Then, the nodes use the geographical position information table to search the neighbor node that meets the requirements for the forward. If a node finds other that meets the communication requirements and set it as the destination node, the node will forward message directly. If not, the node needs to establish candidate node set through the node relationship. Otherwise, the nodes are filtered by the relationship between nodes to obtain the candidate node set. Then, choose those nodes of which the measure value EB is higher than the average as the relay node from the candidate node set for multicopy forwarding.

4.5. Algorithm Implementation of MR-Pareto

(1) Node N initiates the forward request and broadcasts its location information

(2) Evaluate whether any node responds to the forwarding request of the node n. If other nodes respond to node requests, execute (3); Otherwise, abandon this forwarding

(3) Node n and the responding neighbor nodes swap location information; calculate the remaining connection time between nodes T_{test}, and then, execute (4)

(4) Determine the remaining connection threshold between nodes $T_{threshold}$ according to the forwarding message length

(5) Compare the values of the remaining connection time between nodes T_{rest} and the remaining connection threshold between nodes $T_{threshold}$. If $T_{rest} > T_{threshold}$, thus, this node is considered to meet the forwarding condition

(6) Get the relationship between nodes, calculate the center degree, correlation degree, and similarity degree of nodes in the detection set conforming to node position, and then, execute (7).

(7) The Pareto solution set of the objective function composed of three attributes of the nodes is calculated as the candidate nodes set through nondominant ordering

(8) Get the nodes' energy $E_{current}$ and the cache size B among the candidate nodes set

(9) Compare the measurements of node's energy and cache size EB to its mean value. If EB is greater than its mean value, the message is forwarded. Otherwise, ignore this node

5. Performance Evaluation

5.1. Performance Index. In this paper, the simulation software ONE is used as the experimental platform. Moreover, the MR-Pareto routing method is compared with many traditional opportunistic routing methods.

(1) The residual energy is used to evaluate the lifetime of the mobile crowdsensing network, and the average residual energy of the network nodes $energy_{avg}$ is shown in formula (16), where $energy(n_i)$ represents the residual energy of network node n_i

$$energy_{avg} = \frac{\sum_{i=1}^{n} energy(n_i)}{n} \tag{16}$$

(2) The network overhead is expressed as the total number of all message forwarding, as shown in formula (17), where $transmission(M_i)$ is the number of forwards of message M_i

$$overhead = \sum_{i=1}^{m} transmission(M_i) \tag{17}$$

(3) Message delivery rate reflects the situation where messages can be delivered to the destination nodes successfully through collaboration, as shown in

formula (18), where deliver$_c$ount is the number of successfully delivered messages and create$_c$ount indicates the quantity of messages in the network

$$\text{delay}_{\text{pro}} = \frac{\text{deliver}_c\text{ount}}{\text{create}_c\text{ount}} \qquad (18)$$

(4) Packet loss quantity is used to measure the total packet loss quantity of nodes under different routing strategies and congestion control strategies, as shown in formula (19), where drop(n_i) represent the packet loss quantity of node n_i

$$\text{drop} = \sum_{i=1}^{n} \text{drop}(n_i) \qquad (19)$$

5.2. Simulation Environment. Three groups of nodes with different movement speeds were set up in the experiment to compare the network efficiency of the MCS routing strategy. For the first group, the number of nodes was set as 80, and the movement speed was 0.5-1.5 km/h. In the second group, 40 nodes were set, and the movement speed was 2.7-13.9 km/h. The number of nodes in the third group is set to 6, the movement speed is set to 7-10 km/h, and two of them set their transmission range size to 1000 m. The specific parameters are shown in Table 1.

5.3. Simulation Results. The energy of the energy network, network overhead, packet loss quantity, and message delivery rate of the MR-Pareto routing algorithm was further compared under different simulation times. The results of this comparison are reported in Figures 4–7. Other parameters in the simulation parameter setting table remain unchanged, and the performance of each routing strategy is evaluated by changing the simulation time. Gradually increase the simulation time from 6 hours to 18 hours. It is proved that the performance of MR-Pareto routing strategy is better than that of epidemic and prophet traditional routing strategy at different simulation time.

As can be seen from Figure 8, compared with epidemic and prophet routing strategies, the average residual energy of the network significantly improves, especially with the increase of simulation time. In the whole simulation process, the energy consumption of epidemic and prophet routing strategies is approximately equal. When the simulation time was 6 hours, the MR-Pareto routing strategy and the epidemic and prophet routing strategy improved by 2.3% on average, and when the simulation time increased to 18 hours, the MR-Pareto routing strategy and the epidemic and prophet routing strategy improved by 14.2% on average. Since most mobile nodes work continuously and cannot provide power in time, the longer the working time, the more energy can be saved.

Figure 4 illustrates the network overhead of the MR-Pareto, epidemic, and prophet routing strategies over simu-

TABLE 1: User matches with drone.

Parameters name	Parameters values
Scene size	4500 m × 3400 m
First group of nodes	$80 \times (0.5 - 1.5\,\text{km/h})$
Second group of nodes	$40 \times (2.7 - 13.9\,\text{km/h})$
Third group of nodes	$6 \times (7 - 10\,\text{km/h})$
Mobile model of the first group	Random walk movement
Mobile model of the second group	Map route movement
Mobile model of the third group	Map route movement
Transmission range	900 m and 900 m
Bandwidth	250 KBps
Range of message size	$500\,\text{k} - 1\,\text{M}$
Message generation interval	5-15 s, 15-25 s, 25-35 s, 35-45 s, and 45-55 s
TTL	300 min
Node cache	10M, 15M, 20M, 25M, and 30M
Routing strategy	MR-Pareto, direct, epidemic, and prophet
Cache strategy	FIFO
α	100
β	1
Initial energy E	100 J
Scanning energy cost e_s	0.02 J/time
Receiving energy cost e_r	2.4×10^{-7} J/bit
Sending energy cost e_t	3.3×10^{-7} J/bit
Simulation time	12 h

lation time. The epidemic and prophet routing strategies are consistently above 61.5% in the simulation time, while the MR-Pareto routing strategy remains at a relatively low level in terms of network overhead, which remains below 3% in the experiment. As can be seen from the figure, compared with the epidemic and prophet routing strategies, the network overhead of the MR-Pareto routing strategy has decreased by 48.3%. The reason is that the MR-Pareto routing strategy optimizes the selection of relay nodes and reduces the number of messages forwarding and the network resources occupied by message transmission.

In Figure 5, the three routing strategies increase with the simulation time. In the whole simulation process, the epidemic routing strategy has an average 7.2% higher packet loss than the prophet routing strategy. The simulation time of the MR-Pareto routing strategy increased from 6 hours to 12 hours, and the number of lost packets increased from 7,954 to 20,543. MR-Pareto is 37.5% lower than epidemic routing strategy. Compared with prophet, the reduction was 35.8%. The MPOP routing strategy performs well in controlling the number of lost packets.

Figure 6 analyzes the trend of MR-Pareto routing strategy and epidemic and prophet routing strategy over simulation time. When the simulation time is 6 hours, the advantage of MR-Pareto routing strategy is small, but with
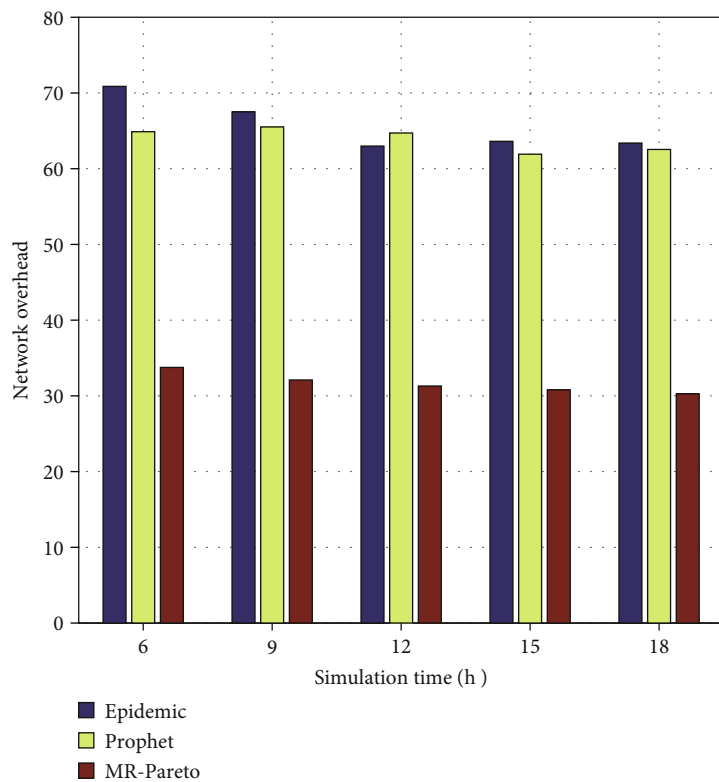
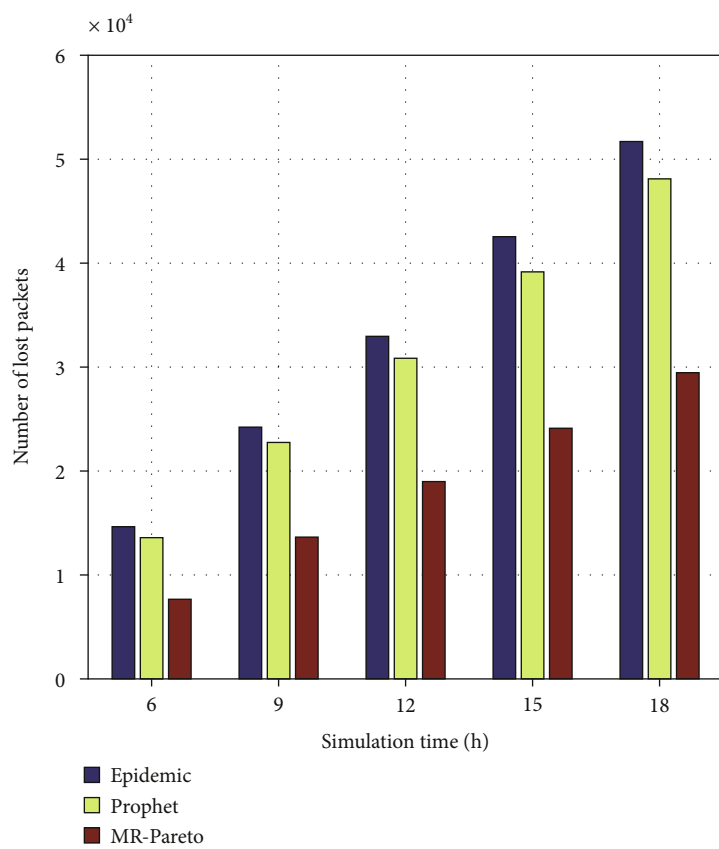FIGURE 4: Network overhead changes with simulation time.

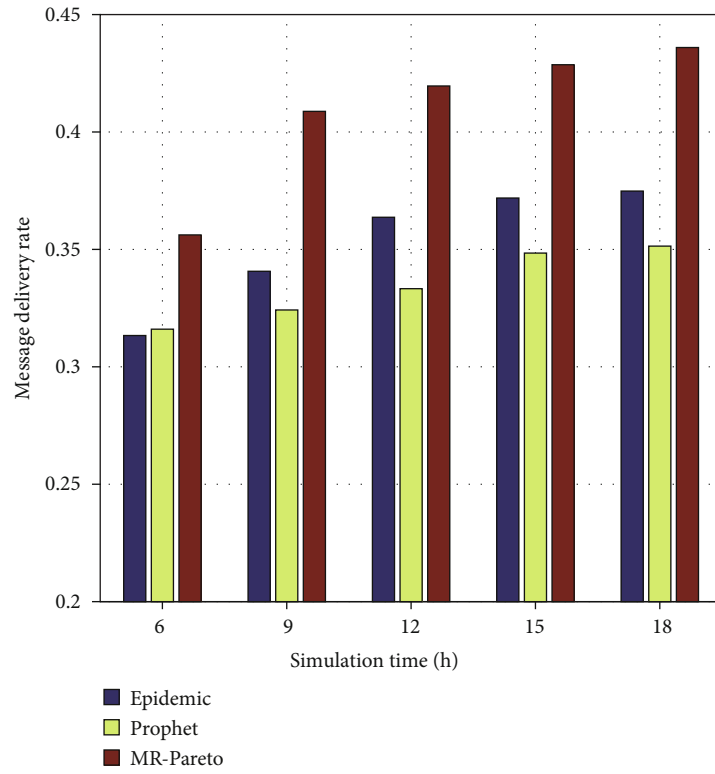FIGURE 5: Number of lost packages change with simulation time.

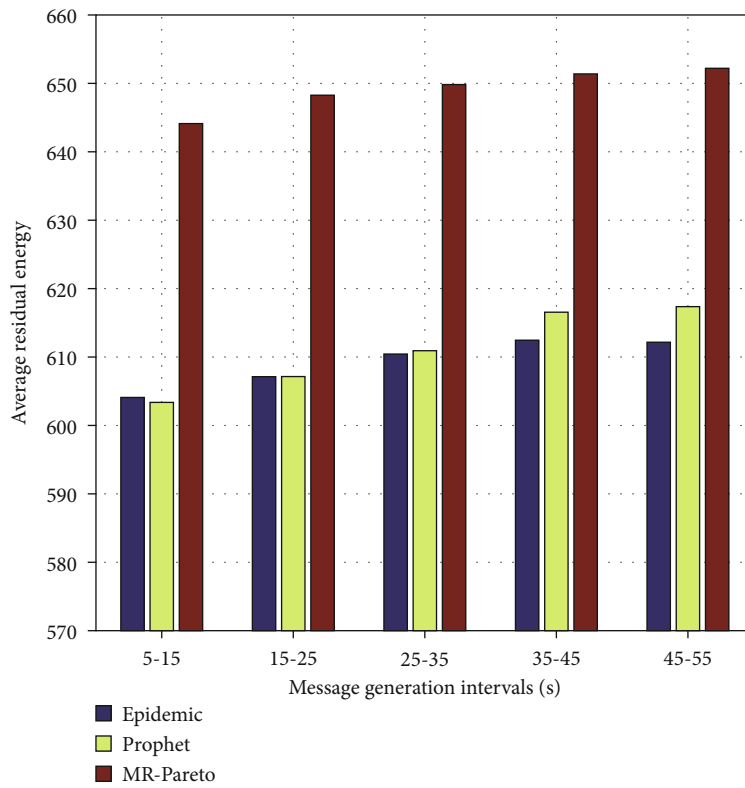Figure 6: Message delivery rate changes with simulation time.

Figure 7: Average residual energy changes with the message generation intervals.
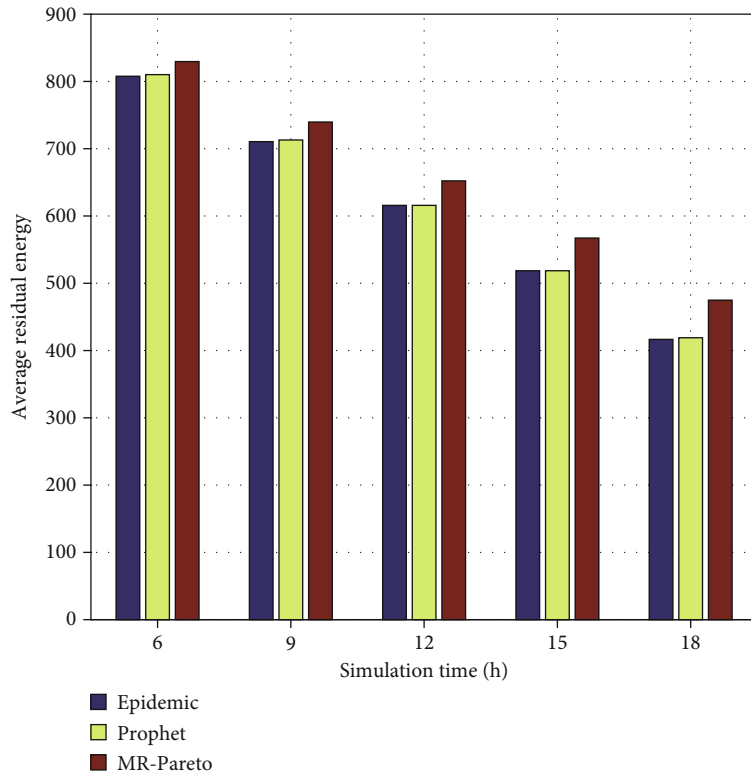
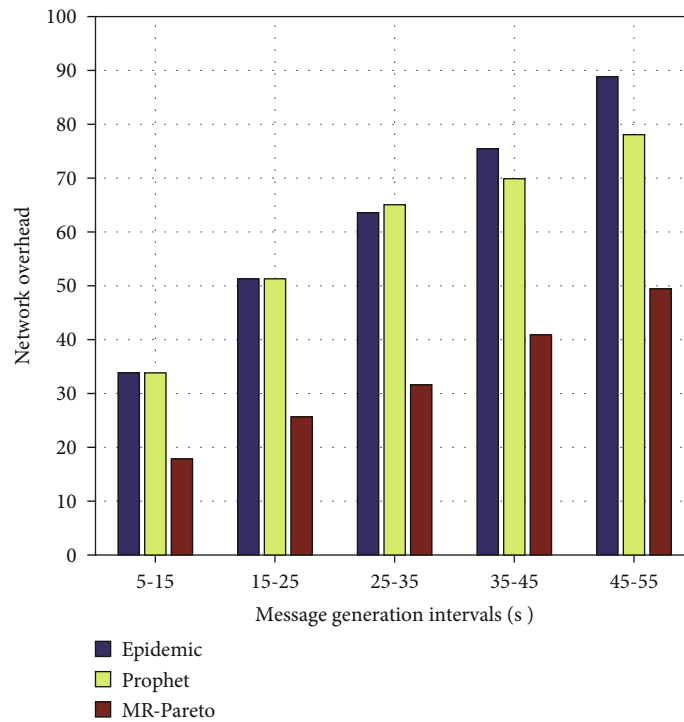FIGURE 8: Average residual energy changes with simulation time.

FIGURE 9: Network overhead changes with the message generation intervals.

the increase of time, the delivery rate of MR-Pareto message keeps higher and higher, staying above 0.4, increasing by 14.1% and 19.2%, respectively, compared with the other two routing strategies. Compared with MR-Pareto, due to the spread and forwarding in the network, epidemic makes all encounter nodes to carry a copy of the message, which
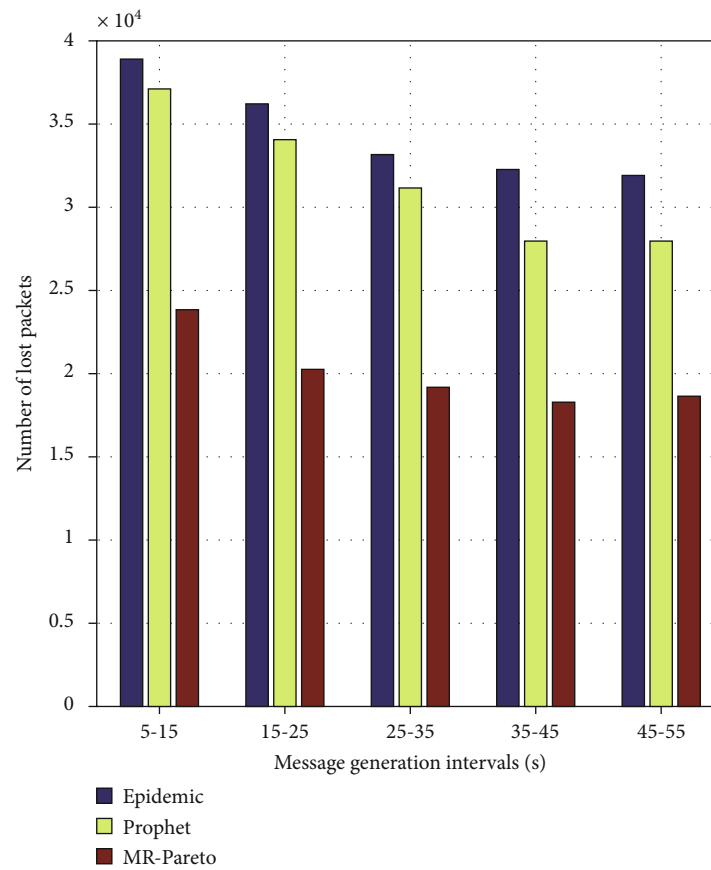
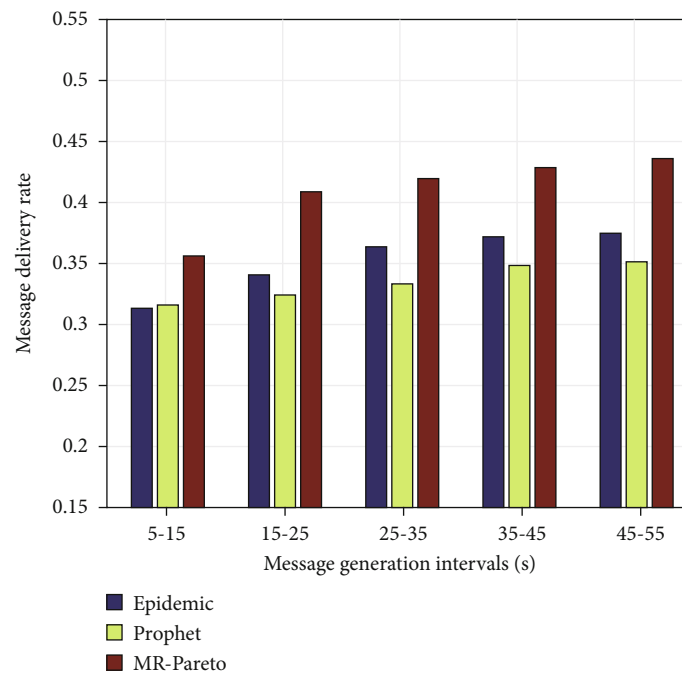FIGURE 10: Number of lost packets changes with the message generation interval.

FIGURE 11: Message delivery rates changes with the message generation intervals.

makes the message delivery rate higher than the prophet routing strategy, but also results in partial meaningless forwarding, which produce a smaller number of successful message delivery to destination nodes than the MR-Pareto routing strategy.

Figure 7–11 presents the residual energy, network overhead, packet loss number, and message delivery rate of the proposed MR-Pareto routing algorithm under various message generation intervals. In order to ensure the efficiency of the simulation, referencing to the simulation parameters set in the table, the MR-Pareto routing algorithm with the other two traditional routing policy performance evaluation, in this paper, consider the MCS intensity produced by the network news; time interval will be generated from 5 to 15 s which gradually increased to 45 to 55 s, to prove that in different time intervals, MR-Pareto routing algorithm compared with the epidemic and prophet traditional routing strategy performance is better.

According to Figure 7, the average residual energy of the three routing strategies increases progressively under the conditions of different message generation intervals, due to the fact that the sensing nodes minimize the generation of new messages and decrease the energy consumption of the nodes during message forwarding and sharing. The epidemic routing strategy is slightly higher than the prophet routing strategy when the message generation density is high but lower than the prophet when the message generation rate is slow. The average MR-Pareto routing strategy is 6.5% and 6.1% higher than epidemic and prophet, respectively.

Figure 9 shows the variation of network overhead with message generation interval between the MR-Pareto, epidemic, and prophet routing strategies. With the decrease of message generation density, the network overhead of the three comparison routing strategies increases gradually. When the time interval of message generation is set at 15-25 s, the gap between epidemic routing strategy and prophet routing strategy increases gradually and remains at a high level. Compared with the other two routing strategies, the network overhead of the MR-Pareto routing strategy is 46.2% lower than that of the traditional epidemic and prophet routing strategies.

It can be seen from Figure 10 that under the circumstance of different message generation intervals, the number of lost packets of the MR-Pareto routing strategy tends to be stable, indicating that it has good stability. The number of lost packets of the three routing strategies decreases gradually because the number of messages generated by the network decreases. The comparison of MR-Pareto routing strategies with respect to epidemic and prophet routing strategies decreased by 34.7% and 32.6%, respectively.

Figure 11 depicts the message delivery rates for different message generation intervals. When the message generation time is 5-15 s, the delivery rate of the MR-Pareto routing strategy is significantly higher than that of the other two routing strategies. It can be concluded that under the condition of relatively large message generation density, the delivery rate of the message is higher. Compared to epidemic and prophet, the MR-Pareto routing strategy has an average improvement of 16.7% and 25.4%, respectively.

6. Conclusion

Given the problem that existing routing strategies fail to combine the spatiotemporal characteristics of nodes, single consideration factors, and subjective intention to balance all attributes in the resource-constrained environment of mobile group-intelligence sensing network, this paper proposed a multiattribute routing method based on Pareto optimal solution. By predicting the location of nodes in communication time, this method evaluates the possibility of nodes becoming node diversity and takes the relationship between nodes as a measuring factor. Pareto optimal method is adopted to calculate the measurement value of nodes becoming candidate nodes. Finally, the message forwarding strategy is determined by combining node energy and cache to realize the optimization of routing method. The simulation results show that, compared to the epidemic and prophet routing strategies, the residual network energy of this routing method increases by 8.3% on average. Moreover, the network performance, such as network overhead, packet loss quantity, and message delivery rate, has also improved. In the case of different message generation intervals, in addition to the overall residual energy of the network increased by 6.3% on average, the network overhead, packet loss quantity, and message delivery rate were significantly improved comparing to the two traditional routing strategies. The MR-Pareto routing method has obvious effect on prolonging network life and improving data forwarding performance.

Data Availability

There is no data set used in this article; the nodes used in the experiment were randomly generated in the simulation environment. In this paper, the specific parameter setting method is given.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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