MPSICA: An intelligent routing recovery scheme for heterogeneous wireless sensor networks

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To address the fault-tolerant recovery problem in a heterogeneous wireless sensor network consisting of several resource-rich supernodes, and a large number of energy-constrained ordinary sensor nodes, we propose a multi-particle-swarm immune cooperative algorithm (MPSICA) to provide intelligent routing recovery scheme. The MPSICA could maintain K disjoint paths from each source node to the nearest supernode and the available path from supernodes to the sink. Moreover, it could investigate the optimal alternative routing strategies, and solve the problem with cloning, high-frequency mutation, clone selection operations, which can improve the fault tolerant ability and reliability of inter-cluster and intra-cluster data transmission. Using this scheme, we can efficiently repair the broken path of intercluster supernodes or intracluster ordinary nodes network. Finally, we discuss the implementation of the MPSICA based fault-tolerant routing protocol and present the performance evaluation through experiments. The simulation results have verified that the MPSICA based protocol can provide reliable communication with intelligent bio-heuristic routing recovery scheme, thus extend the lifetime of WSNs.

1. Introduction

Internet is extending its reach to the real world through innovations collectively termed the Internet of Things (IoT) [26,28,33]. As the important role of the IoT, wireless sensor networks (WSNs), especially heterogeneous ones, have been attracting growing research interests due to their ability of collecting data from the environment [12,29]. The heterogeneous WSNs usually consist of two types of wireless devices [2]: resource-constrained ordinary wireless sensor nodes randomly deployed with a large number, and a much smaller number of resource-rich supernodes placed at known locations. All the ordinary nodes in the heterogeneous WSNs possess the same communication, energy, bandwidth, and capability. The supernode network, which provides more energy, transmission bandwidth, and computing ability, is used to quickly forward sensor data packets to the sink [11]. The heterogeneous WSNs can significantly improve the successful delivery rate, reduce the energy consumption of data delivery, thus effectively extend the network lifetime [19,21].

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However, unpredictable events such as communication link broken and battery depletion would make the ordinary sensor devices fail, partitioning the network and disrupting ordinary network functions. Therefore, fault tolerance becomes a critical issue for the successful communication of heterogeneous WSNs. It is expected that the network topology broken caused by software or hardware failure of intra-cluster nodes or inter-cluster supernodes could be automatically reconstructed and self-healed with the fault-tolerant routing technology.

A number of fault-tolerant routing protocols for homogeneous and heterogeneous WSNs [8,12,27] have been developed. For homogeneous WSNs, the most common solution is to establish disjoint multipaths which are node/link disjoint with the previous path and with other alternative paths [25]. Thus a failure in any or all nodes/links on the previous path does not affect the alternative paths [14]. For heterogeneous WSNs, two-layered heterogeneous WSNs are proposed which have better scalability and lower overall cost [7,30]. As we known, in the heterogeneous WSNs, all the nodes only need to transmit data to the nearest supernodes, which indirectly shorten the transmission distance between source nodes and the sink, and extend their lifetime. In [19], an energy efficient heterogeneous clustered scheme (EEHC) for WSNs was proposed. Boukerche and Martirosyan [6] used an inter-cluster communication (ICE) based energy aware and fault tolerant protocol by alternating the nodes responsible for inter-cluster communication inside one cluster. Hamadi and Ing-Ray [13] proposed a multipath routing protocol for intrusion tolerance of heterogeneous WSNs so that the query response success probability is maximized while extending the network lifetime. The protocol exploits the tradeoff between energy consumption vs the gain in reliability, timeliness, and security. However in these traditional protocols, the routing recovery scheme for path failure, especially the failures of both supernodes and ordinary sensor nodes in the heterogeneous network have rarely been simultaneously considered.

In this paper, we propose a scheme to solve the constrained non-convex optimization problem by using the particle swarm computing algorithm. Our work embodies in the following aspects: (1) we consider a heterogeneous WSNs architecture with several supernodes and concern with providing K-disjoint path from each source node to the nearest supernode through multi-hop relay nodes; (2) a fault-tolerant routing protocol with a multi-particle-swarm immune cooperative algorithm (MPSICA) is proposed, it provides fast routing recovery with alternative path for solving problems of intra-cluster ordinary node and inter-cluster supernode failure. Using this scheme, the heterogeneous WSNs can tolerate the failure of ordinary node paths or supernode paths, so that the traditional retransmissions can be decreased and reliability can be improved with lower energy consumption and longer lifetime.

The contributions of this paper compared with our previous article [16] are as follows: (1) we consider a static two-layer heterogeneous network model, comparing with that mobile sink homogeneous network model in [16], which is a mobile WSNs; (2) we provide routing recovery scheme and protocol dealing with alternative path for both intra-cluster ordinary node and inter-cluster supernode failure, the previous work only deals with the path failure of mobile network caused by the moving sink; (3) the fault-tolerant routing protocol adopts a multi-particle-swarm immune cooperative algorithm (MPSICA), which can provide more efficiency, higher convergence speed and diversity characteristic to get the optimal path solution. We also select the protocols of ICE and EEHC to compare with our approach, as the ICE and EEHC are both effective fault-tolerant routing protocols for heterogeneous WSNs, and they have both low energy depletion ratio and packet loss ratio.

This content of the rest of the paper is organized as follows. The heterogeneous WSNs and the fault model are depicted in Section 2. Section 3 presents the MPSICA based solution for the fault-tolerant routing recovery problem. The simulation results on performance evaluation of our scheme with other protocols are covered thoroughly in Section 4. Finally, the paper is concluded in Section 5 where entire work has been provided in a summary with mention of areas for further improvements in the future.

2. Model of the heterogeneous WSNs

2.1. The architecture for the heterogeneous WSNs

The architecture of heterogeneous WSNs contains two types of wireless sensors, as shown in Fig. 1. The lower layer is formed by intra-cluster ordinary sensor nodes with constrained resource, including small amount of source nodes and large amount of relay nodes [22]. The main tasks of source nodes are data sensing, processing, and transmission. The tasks of relay nodes are data processing and relaying. Their primary energy consumption source is the radio transceiver. The upper layer of network consists of resource-rich inter-cluster supernodes, and each supernode is a cluster head of surrounding ordinary nodes. Wireless communication links between inter-cluster supernodes have considerably longer ranges and higher data rates, allowing the supernode network to bridge remote regions of the interested area. The tasks performed by a supernode are relaying data from ordinary sensor nodes to the sink, data aggregation, and complex computations. The proposed MPSICA is performed by the supernodes. Therefore, data transmission and collection in the heterogeneous WSNs have two steps: Firstly, ordinary nodes transmit information on multihop paths toward the cluster head supernode; Later, the packet is forwarded to the sink using fast supernode-to-supernode communication. The nomenclature of used symbols in the network is provided in Table 1.

The heterogeneous WSNs contain $M_{sup}$ supernodes and $M_{node}$ ordinary sensor nodes, and $M_{sup} << M_{node}$. As shown in Fig. 1, each ordinary node or relay node is connected to the nearest supernode, thus several clusters are formed and...
supernodes are considered as cluster heads. Supernodes (nodes 1, 2, ..., 12) are interconnected to form a minimum transmission spanning tree. The supernodes on the tree will deliver multihop aggregated data to the sink (node 13). The network has the following characters: (1) the network is static, where the nodes are static after deployed; (2) each node knows the location of itself, the supernodes and the sink. The location can be obtained by GPS or localization protocols for estimating the location of a node; (3) the wireless transmission energy of supernode can be adjusted according to the distance between itself and next-hop node.

The energy model is proposed as follows. We calculate the transmit energy $\text{ene}_T(b, d_{ij})$ of $b$ bits packet transmitted from the relay node $i$ to another node $j$ ($1 \leq i \leq n$, $1 \leq j \leq n$, $i \neq j$) with the following model [1].

$$\text{ene}_T(b, d_{ij}) = \alpha_1 b + \beta b d_{ij}^m$$

where $d_{ij}$ is the distance between node $i$ and node $j$. $\alpha_1$ is the transmit energy coefficient, $\beta$ is the amplifier coefficient and $m$ is the path loss exponent, $2 \leq m \leq 4$. Similarly, the receive energy $\text{ene}_R(b)$ of $b$ bits packet transmitted by the relay node $i$ is defined as:

$$\text{ene}_R(b) = \alpha_2 b$$

where $\alpha_2$ is the receive energy coefficient. Hence, we calculate $\text{ene}_i$, the total energy consumption of relay node $i$ for data gathering as $\text{ene}_i = \text{ene}_{T_i} + \text{ene}_{R_i}$. We also define $\text{ene}_{DF}$ and $\text{ene}_{RT}$ as energy consumption of data fusion and updating routing table. For the MPSICA, the energy consumption of master–slave particle update, immune clone, mutation, particle selection, and restrain are defined as $\text{ene}_{PU}$, $\text{ene}_{IC}$, $\text{ene}_{IM}$, $\text{ene}_{PS}$, and $\text{ene}_{PR}$ per iteration, respectively. Using this energy model, the total energy consumption of data transmission and performing the proposed algorithm in each round can be evaluated in the simulation.
We also introduce a simple fault model adopted in [9]. The probability of intra-cluster ordinary nodes failure is given by \( \text{Pro}_{\text{node}} \). As we use the more reliable supernodes to gather and transmit data at a lower failure probability, the supernode is more resilient to failures. Therefore, the probability of inter-cluster supernode failure is assumed to be \( \text{Pro}_{\text{sup}} \), and \( \text{Pro}_{\text{sup}} << \text{Pro}_{\text{node}} \). If any ordinary node or supernode fails, the routing recovery scheme for solving intra-cluster or inter-cluster node failure would be performed.

2.2. Architecture for K-disjoint-path intra-cluster network

The network is modeled as a connected graph \( G(N(v), N(e)) \). \( N(v) \) is a finite set of network nodes and \( N(e) \) is the set of network links interconnecting these nodes, in which source node \( v_s \in N(v) \) and supernode (cluster head) \( v_{ch} \in N(v) \). \( p_i(s, ch) \) is a valid path between \( v_s \) and \( v_{ch} \). \( N(p_i(s, ch)) \) denotes the set of all the valid paths between \( v_s \) and \( v_{ch} \). \( p_i(s, ch) \in N(p(s, ch)) \). \( v (v \in p_i(s, ch)) \) represents a node in \( p_i(s, ch) \). \( e (e \in p_i(s, ch)) \) represents the direct link between any two adjacent nodes in \( p_i(s, ch) \). The factors affecting the choice of path \( p_i(s, ch) \) include: delay function \( \text{delay}(e) \), distance function \( \text{dist}(e) \), energy consumption function \( \text{ene}(e) \) of the link between adjacent nodes, and available residual energy function \( \text{Rene}(v) \) of each node. Then these parameters can determine the fitness function of \( p_i(s, ch) \). \( \text{fitness}(p_i) \):

\[
\text{fitness}(p_i) = \frac{\sum_{e \in p_i(s, ch)} \text{Rene}(v) - \sum_{e \in p_i(s, ch)} \text{ene}(e)}{\sum_{e \in p_i(s, ch)} \text{ene}(e) + \sum_{e \in p_i(s, ch)} \text{dist}(e) + \sum_{e \in p_i(s, ch)} \text{delay}(e)}
\]

where \( \omega_1 \) is the adjustable weight of the normalized ratio of \( p_i(s, ch) \)’s energy consumption with total links’ energy consumption, \( \omega_2 \) means the adjustable weight of the normalized ratio of \( p_i(s, ch) \)’s delay with total links’ delay, and \( \omega_3 \) specifies the adjustable weight of the normalized ratio of \( p_i(s, ch) \)’s distance with total links’ distance in the fitness function, and \( \omega_1 + \omega_2 + \omega_3 = 1 \). If \( \omega_1 \) is higher, we prefer the paths with less energy consumption, and a higher value of \( \omega_2 \) increases the chance for us to choose the paths with less delay, higher value of \( \omega_3 \) makes the path with shorter distance more suitable. Here, we select \( \omega_1 = 0.4 \), \( \omega_2 = 0.2 \), \( \omega_3 = 0.4 \), which means that the less energy consumption and shorter distance would make the alternative path more suitable.

As illustrated in Fig. 2, we assume \( K = 3 \), and the \( K \) disjoint paths from source node \( v_1 \) (node 2) to cluster head \( v_{ch} \) (node 40) are 2–6–11–16–22–40, 2–7–12–17–40, and 2–8–13–18–40. The detailed protocol dealing with routing recovery problem is presented in the following sections.

3. The MPSICA based fault-tolerant routing protocol for heterogeneous WSNs

3.1. The swarm intelligence and MPSICA for routing recovery

Swarm intelligence has provided new avenues in the field of optimization. Bonabeau defined Swarm intelligence as the attempt to design algorithms or distributed problem-solving devices inspired by collective behavior of social insect colonies and other animal societies [3]. Common examples range from colony of bees to flock of birds. The main essence of swarm intelligence is properly including the functional behavior of these group agents into a practical computational model [10], such as Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) algorithms. ABC proposed by D. Karaboga, is based

![Fig. 2. K-disjoint-path intra-cluster spanning graph.](image-url)
on the minimal foraging model of honey bees used in nectar collection from the adjoining environment of their honeycomb [4], with the behavior like self-organization, task allocation and communication among the individuals.

One of the most popular forms of swarm intelligence lies in the PSO [24]. Devised on the modeling of bird flocking, PSO implements a stochastic optimization technique. It is recently one of the primary interests of researchers in the domain of swarm intelligence. Comparing with the ABC, the PSO needs fewer parameters to adjust, and has been applied in the routing protocols of WSNs [16,18] more frequently.

In this paper, the algorithm dealing with the fault-routing problem of the WSNs should support the characteristic of low energy consumption. Therefore, we propose the light-weight PSO due to its simplicity, fast convergence, and not heavy computational burden [18]. In the PSO, each particle is a potential solution to the problem. Assume $N$ particles fly in the $D$-dimensional search space, the position of the $i$-th particle is $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})^T$, and its velocity is $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})^T$. $P_i = (P_{i1}, P_{i2}, \ldots, P_{iD})$ is the best previous position of the particle, and $P_g$ is the global best position of the whole particle swarm [15]. Therefore in each time step $t$, the velocity $V$ and position $X$ of each particle are updated according to Eqs. (4) and (5):

$$V_{id}(t + 1) = wV_{id}(t) + c_1\text{Rand}_1(P_{id} - X_{id}(t)) + c_2\text{Rand}_2(P_g - X_{id}(t))$$

$$X_{id}(t + 1) = X_{id}(t) + V_{id}(t)$$

where $c_1$, $c_2$ are learning factors, and we select $c_1 = c_2 = 2$. $\text{Rand}_1$ and $\text{Rand}_2$ are random numbers uniformly distributed in $[0, 1]$; $w$ is the inertia weight and can control the balance between the global and local exploration ability of the swarm.

PSO suffers from disadvantages in the form of narrow search zone and slow convergence, the diversity of population decreases in the late stage of evolution, and its convergence would stop when obtaining a local optimal solution. Yen and Leong [32] proposed a multi-population PSO, which used cooperative behavior of multiple swarms to improve traditional PSO, called CPSO. Another important modification of PSO is the constriction factor PSO (CFPSO) [17], where $K$ is called constriction factor, as described in the Eqs. (6) and (7).

$$V_{id}(t + 1) = K(V_{id}(t) + c_1\text{Rand}_1(P_{id} - X_{id}(t)) + c_2\text{Rand}_2(P_g - X_{id}(t)))$$

$$K = 2 / \left[2 - \varphi + \sqrt{\varphi^2 - 4\varphi}\right] (\varphi = c_1 + c_2, \varphi > 4)$$

Niu and Zhu [23] introduced a slave–master swarm cooperative scheme to PSO (MCPSO) to balance the global and local exploration. It is a master–slave model that consists of one master swarm and several slave swarms. Slave swarm focuses on local exploration. It is a master–slave model that consists of one master swarm and several slave swarms. Slave swarm focuses on local exploration.

However, the MCPSO still uses the idea of the traditional PSO to evolve. The capability of each particle yielding high diversity to increase search space needs to be improved. Therefore, we draw on outstanding diversity characteristic of immune mechanism and develop the algorithm MPSICA. Each particle is considered as an antibody. After the antibody clone and selection, the more suitable one maintains in the sub swarm and the less suitable one is restrained. In the MPSICA, mutation direction of the particle (antibody) is determined by evolution equation, and immune mechanism increases its diversity. The MPSICA is the kernel of our fault-tolerant routing protocol. The detailed procedures of the MPSICA are described as follows.

1. **Initialization**: Initialize master and slave particle swarm parameters.

   The principle of the MPSICA is to search the solution in different $D$-dimensional target spaces using several particle swarms, respectively. Initially, $n$ particles are divided into $k$ swarms, containing one master swarm and $k – 1$ slave swarms ($1 < k < n$). Each swarm contains $[n/k]$ particles with random positions and velocities in $D$ dimensions.

2. **Immunization**: Immune clone, mutation, selection and restrain of particles.

   In this step, each particle is an antibody. The sequence number $NS$ of particle $i$ arranged in the optimal solution set $X_S$ is considered as the affinity $PA_i$ of the particle:

   $$PA_i = NS$$

   Then the clone number $CN_i$ is calculated as follows:

   $$CN_i = PA_i \times N_p / \left[ \sum_{j=1}^{m} j \right]$$

(10)

(11)
where ⌈·⌉ represents round up, Np is the particle number, m is the size of optimal solution set Xb, and the total cloned particle number is \( \text{Sum} = \sum_{i=1}^{N} CN_i \). Therefore, the clone number is proportional to the particle fitness. Then the particle mutation is used in the clone populations, the mutation rule is as follow:

\[
PC_i = X_i + \alpha \text{Rand}
\]  

(12)

where \( PC_i \) is the clonal individual, \( X_i \) is the original antibody, \( \alpha \) represents mutation factors, here we select \( \alpha = 0.5 \). \( \text{Rand} \) is uniformly distributed in \([0,1] \).

In the particles restrain rule, we calculate the antigen stimulus degree of the particles in \( N(X_p) \) and the mutation particles. The Euclidean distance between particle \( N(PC_i) \) and antigen (fitness function) \( \text{fitness}(X_i) \) is

\[
D(i,j) = \sqrt{\sum_{i=1}^{n} (PC_{ai} - \text{fitness}(X_{ai}))^2}.
\]

Therefore the stimulus degree of antibody (particle) is:

\[
PS(i,j) = 1/D(i,j) = 1/\sqrt{\sum_{i=1}^{n} (PC_{ai} - \text{fitness}(X_{ai}))^2}.
\]  

(13)

Then we compare each particle with the stimulus threshold \( T_h \), the worse particle \( (PS(i,j) < T_h) \) is restrained, and the better particle would maintain in the memory cell.

(3) Termination criterion.

If the solution is satisfied with the termination criterion: The fitness that we have obtained is the optimal (largest) fitness \( \text{fitness}(\cdot) \), or iterations \( I_{\text{gen}} \) decreases to zero, then the optimal path \( p_i \) will be the desired optimal solution. The global optimal fitness of the whole particle swarm outputs, and this procedure ends, otherwise goto Step 4. Thereafter the optimal routing path is established.

(4) Update: Update the particle states in master and slave swarms.

In this step, the velocity and position of particles in the slave swarms are updated according to Eqs. (4) and (5), and the velocity and position of particles in the master swarm are updated according to Eqs. (8) and (9). \( w \) plays an important role in the convergence of the result among the adjustable parameters. To improve the convergent performance, the classical linearly decreasing weight strategy (LDW) for \( w \) is used, as shown in Eq. (14). \( t_{\text{max}} \) is the maximum iteration number, here we select \( w_{\text{max}} = 0.85 \). \( w_{\text{min}} = 0.35 \).

\[
w(t) = w_{\text{min}} + \frac{w_{\text{max}} - w_{\text{min}}}{t_{\text{max}}} \times (t_{\text{max}} - t).
\]  

(14)

3.2. The MPSICA based fault-tolerant routing protocol

To deal with the path failure problem due to nodes’ physical damage or energy depletion, the MPSICA will calculate fitness to provide an intelligent routing recovery scheme with an alternative optimal-fitness path. As we know, the alternative path with more available energy, less distance, less energy consumption and less delay from source node though supernodes to the sink is better. For this reason, the fitness functions and the process of protocol for intra-cluster and inter-cluster nodes’ routing recovery are described as follows. In this network, downstream is defined as the “to-the-sink” direction, while upstream refers to the opposite.

(1) The routing protocol for intra-cluster ordinary node failure.

\( v_{\text{fail}} \) (node 13) is a failed relay node in the cluster. Once it is failed, as illustrated in Fig. 2, the supernode \( v_{\text{ch}} \) (node 40, here we use cluster head symbol \( v_{\text{ch}} \) to replace the symbol \( v_{\text{sup}} \) in the intra-cluster) will construct sub-graph \( G \) \((G \subset G)\) according to the supernode’s current topology information, and extract the set of nodes \( N_{\text{node}} \) which would be used to construct an alternative path \( p_i(s, ch) \) from \( G \). Each node represents a particle, and the population size of particle is \( n \). Some nodes of \( N_{\text{node}} \) can form a particle sequence \( \{ v_{p1}, v_{p2}, \ldots, v_{pm} \} (m \leq n) \) according to their order, which can construct a path \( p_i(s, ch) \) from source \( v_i \) to \( v_{\text{ch}} \). The MPSICA would optimize the particle sequence to obtain the optimal path \( p_i(s, ch) \) with optimal fitness \( \text{fitness}(p_i) \) according to Eq. (3). The path \( p_i(s, ch) \) includes the following nodes \( \{ v_i, v_{p1}, v_{p2}, \ldots, v_{pm}, v_{\text{ch}} \} \).

(2) The routing protocol for inter-cluster supernode failure.

If a supernode \( v_{\text{fail}} \) (node 7) fails, as illustrated in Fig. 1, its upstream supernodes \( v_{\text{fail}..} \) (node 8 or 9) will select another supernode to play \( v_{\text{fail}} \’s \) role using MPSICA based protocol. The process can be divided into two steps:

(a) Each \( v_{\text{fail}..} \) selects a node from its surrounding supernodes as its upstream node. Revisit the heterogeneous WSNs in Fig. 1, \( N(v_{\text{sup}}) \) represents the set of possible suitable supernodes, and each \( v_{\text{sup}} (v_{\text{sup}} \in N(v_{\text{sup}})) \) maintains its information of previous path \( p_i(sup, sink) \) to the sink \( \{ v_{sup1}, \ldots, v_{sink} \} \). Then \( v_{\text{fail}..} \) is added to the path, and forms the new path \( p_i(fail - u, sink) \) containing nodes \( \{ v_{\text{fail}..}, v_{\text{sup}1}, \ldots, v_{\text{sink}} \} \). Therefore the new path set formed by \( N(v_{\text{sup}}) \) is \( N(p(fail - u, sink)) \). Then each path \( p_i(fail - u, sink) \) is considered as a particle, and \( v_{\text{fail}..} \) selects a supernode \( v_{\text{sup}} \) as its downstream supernode with optimal fitness \( \text{fitness}(sup) \) from the whole particles using the MPSICA. Therefore, the alternative path would be generated (such as paths 8–9–13, and 12–11–9–13 in Fig. 1). The fitness \( \text{fitness}(sup) \) is as follows:
fitness\(sup\) = \(\frac{\sum_{v: p_i(fail - u, sink)} Rene(v)}{\alpha_1 \sum_{r_to_r: fail - u, max\_ene(r)} e\_ene(r) + \alpha_2 \sum_{r_to_r: fail - u, max\_delay(r)} e\_delay(r) + \alpha_3 \sum_{r_to_r: fail - u, max\_dist(r)} e\_dist(r)}\)

where \(\alpha_1\), \(\alpha_2\) and \(\alpha_3\) is respectively the adjustable weight of the normalized ratio of \(p_i(fail - u, sink)\)’s energy consumption, delay and distance with total links’ energy consumption, delay and distance in the fitness function, \(\alpha_1 + \alpha_2 + \alpha_3 = 1\). Here we select \(\alpha_1 = 0.4\), \(\alpha_2 = 0.2\), \(\alpha_3 = 0.4\), \(ene\_e\), \(delay\_e\) and \(dist\_e\) are energy consumption cost, time delay, and distance between two adjacent supernodes on \(p_i(fail - u, sink)\). The higher value of fitness\(sup\) indicates the better downstream supernode.

(b) After that, the set of all the source nodes \(N(v\_fail - x)\) belonging to failed supernode \(v\_fail\) would select another supernode from the surrounding supernodes as their new cluster head. The downstream supernode \(v\_fail - d\) (node 13, the sink in Fig. 1) of \(v\_fail\) collects the information of \(N(v\_fail - x)\) and the set of surrounding supernodes \(N(v\_ch)\), and considers each supernode \(v\_ch\) \((v\_ch \in N(v\_ch))\) as a particle. Then \(v\_fail - d\) selects a supernode \(v\_ch\) with optimal fitness \(fitness(ch)\) from the whole particles using the MPSICA, and considers it as the best cluster head of \(N(v\_fail - x)\).

The fitness function is defined by:

\[
\begin{align*}
fitness(ch) &= \omega_1 f_1 + \omega_2 f_2 \\
f_1 &= \sum_{fail - x < ch} Rene(v\_fail - x) / Rene(v\_ch) \\
f_2 &= \sum_{fail - x < ch} dist(v\_fail - x, v\_ch) / C(v\_fail - x)
\end{align*}
\]

where \(f_1\) is the average distance from the set \(N(v\_fail - x)\) to \(v\_ch\), \(C(v\_fail - x)\) is the total node number of \(N(v\_fail - x)\). \(f_2\) is the ratio of total available residual energy of all nodes in the network with the available energy of \(v\_ch\). \(\omega_1\), \(\omega_2\) specify the respective adjustable weights of \(f_1\), \(f_2\) in the fitness function, and \(\omega_1 + \omega_2 = 1\). Here we select \(\omega_1 = 0.6\), \(\omega_2 = 0.4\).

### 4. Simulation result

#### 4.1. Simulation model

To evaluate the performance of the MPSICA, the simulation was carried out under the following platform configurations, and the results are compared with the protocols ICE and EEHC.

Software: MATLAB 2008a (version 7.6.0); Processor: Intel i7-4600M; CPU Speed: 2.90 GHz; Memory: 4 GB DDR3 RAM; Operating System: MS Windows 7.

Before conducting simulation experiments, we need to configure the simulation environment: 50–500 ordinary sensor nodes are randomly deployed on a two-dimensional plane \((10,000 \times 10,000\) m\(^2\)). We assume that the ordinary nodes are homogeneous and have the same energy of 120 J. Their sensing radius is 300 m, communication radius is 600 m, and the largest bandwidth of the homogeneous WSNs is 200 kb/s. In contrast, several supernodes are located at known coordinates, which together can cover all the ordinary nodes in the network. Their communication radius is 2500 m. The number of disjoint multipath from each source node to the nearest supernode is \(K = 3\). The probabilities of intra-cluster node failure and inter-cluster supernode failure are initially set \(Pro\_node = 0.01\) and \(Pro\_sup = 0.0005\), and a fixed number of packets would be sent to the sink in each round. According to the description of energy model in Section 2.1, we select, \(a_1 = 30\) nJ/bit, \(b = 60\) nJ/bit, \(a_2 = 150\) pJ/bit/m\(^2\), \(m = 2\), \(ene_{p_j} = 4\) nJ/bit, \(ene_{r} = 2\) nJ/bit, and for the MPSICA, \(ene_{p_j} = 80\) pJ, \(ene_{res} = 5\) pJ, \(ene_{IM} = 10\) pJ, \(ene_{PS} = 15\) pJ, \(ene_{RT} = 10\) pJ per iteration. The parameters used for the MPSICA are: \(D = 30\), \(I_{Gen} = 800\).

#### 4.2. Evaluation of the experimental results

The simulation parameters are given: 200 data packets will be sent from all source nodes to the sink in each round, until the recovery scheme cannot maintain the effective communication of the network and sink cannot receive packets at all. Each packet size is 10 k. The numbers of supernodes and source nodes account for 8% and 10% of the total number of nodes. To illustrate the effect of the proposed protocol, we take several snapshots during the simulation. Fig. 3(a) shows a small area \((2000 \times 2000\) m\(^2\)) which illustrates a cluster with the existed 3 intra-cluster paths from source node (node 29) to supernode (node 18). We can see when an intermediate node (node 1) is failed, source node immediately establishes an alternative path to connect the supernode, so as to replace the 3rd path. Fig. 3(b) shows a larger area \((7000 \times 7000\) m\(^2\)) which illustrates the whole network with one existed inter-cluster path from a supernode (node 1) to the sink. We can see once an intermediate supernode (node 6) fails, node 1 immediately establishes an alternative path to connect the sink, so as to replace the previous path. The simulation results are illustrated in Figs. 4–6.

As defined, one time of simulation will last 800 rounds. In Fig. 4(a–c), the x-axis represents the number of rounds in one time of simulation, the y-axis represents the average energy depletion ratio \((consumed\ energy\ of\ nodes\ vs\ initial\ energy\ of\ nodes)\) [31] after 10 times of simulation. We can see that energy depletion ratio of the MPSICA based protocol is 5–10%.
smaller than that of the EEHC and the ICE. Each source node is \( K \)-disjoint-path supernode connected and the total energy consumed is minimized. Secondly, although the MPSICA would consume a part of energy to implement optimized search, the MPSICA can select the nodes with better QoS parameters (e.g. more residual energy and less delay) to establish alternative path. It would construct a more reliable transmission environment to reduce the retransmission caused by unstable

Fig. 3. Snapshot of establishing the alternative path generated by the MPSICA.

![Intra-cluster routing recovery](image1)

![Inter-cluster routing recovery](image2)

(a) Intra-cluster routing recovery  (b) Inter-cluster routing recovery

Fig. 4. Ratio of energy depletion per round with different network scale.

![Energy depletion ratio](image3)

![Energy depletion ratio](image4)

(a) 100 nodes  (b) 200 nodes  (c) 400 nodes

Fig. 4. Ratio of energy depletion per round with different network scale.
paths, and therefore save energy and extend the network lifetime. And the energy dispersion of the protocols is increased as the size of the network is expanded in Fig. 4(a–c), which indicates that the larger scale of network nodes would lengthen the routing path, make the routing less stable and consume more energy.

In Fig. 5(a–c), the x-axis indicates the number of rounds in one time of simulation, the y-axis indicates the current node survival ratio (number of current alive nodes vs total number of nodes). The node survival ratio in the MPSICA is 5–8% more than the EEHC and the ICE from the simulation result. With the increase of network nodes number, the node survival ratio is decreased. This demonstrates that the MPSICA reduces the network communication overhead and energy consumption with the efficient intelligent routing recovery scheme, so that ordinary nodes and supernodes would extend their lifetime. At the same time, since the increase of network nodes number would lengthen the average effective length of the path, the probability of path failure is also increased. It speeds up the energy consumption of supernodes performing routing recovery algorithm, so that the node survival ratio is reduced. But the node survival ratio of the MPSICA is still the highest.

In Fig. 6(a–c), the x-axis represents the number of network nodes, the y-axis represents the average packet delivery ratio after 10 times of simulation. From Fig. 6(a), we can see that the heterogeneous WSNs with the MPSICA can forward more packets to the sink than the network with ICE and EEHC over the same number of rounds. In most cases, the MPSICA can send 4–12% more packets to the sink. This is because that the MPSICA provides an intelligent routing recovery scheme from path failure with an optimal alternative path, which improves the successful delivery rate. Note that the packet delivery ratio (number of successfully delivered packet vs required packet) always decreases as the size of the network is extended, which indicates that the larger network scale will lengthen the routing path from source to sink and increase the packet loss rate.

We also compare the performance trends of the three algorithms with different failure probabilities of ordinary node or supernode. Then we analyze and compare the packet delivery ratio against the number of network nodes in Fig. 6(a) and (b). The observed packet delivery ratio of the proposed schemes degrades when \( \text{Pro}_{\text{node}} \) ascends from 0.01 to 0.02 and \( \text{Pro}_{\text{sup}} \) maintains \( \text{Pro}_{\text{sup}} = 0.0002 \). It means that the performance of proposed protocol is decreased as the percentage of failed nodes increases over the same number of rounds. This performance would be decreased more obviously when the value of \( \text{Pro}_{\text{sup}} \) is doubled by comparing Fig. 6(b) and (c). However, the packet delivery performance of the MPSICA is still the best, though their gap is becoming smaller.
Fig. 7 shows the average delay of each packet delivered from source node to the sink, which can indirectly indicate the computational time of different protocols. The less delay would mean the shorter computational time. The x-axis is the number of network nodes, the y-axis represents the average delay of packet delivery after 10 times of simulation. The node failure probabilities are assumed as $P_{\text{node}}=0.02$ and $P_{\text{sup}}=0.0004$, which are the same as those in Fig. 6(c). We can observe that the MPSICA outperforms the ICE and the EEHC in terms of average delay for the same networks. The MPSICA can still demonstrate lower delay when network scale grows. A lower delay of packets can be explained by the faster supernode

![Fig. 7. Delay of packet delivery with different nodes number.](image-url)
communication routing and shorter alternative path selection of the proposed MPSICA-based protocol for fault tolerance. Using this scheme, our protocol can obtain less computational time among these protocols.

5. Conclusions

In this paper, we presented a routing recovery model of heterogeneous WSNs with providing K-disjoint-path from each source node to the nearest supernodes, and available path from supernodes to the sink, then we proposed the MPSICA based fault-tolerant routing protocol for the model. The multi-particle-swarm immune cooperative algorithm focuses on a solution dealing with the problem of energy depletion of ordinary nodes or supernodes. It tries to establish an adaptive and robust transmission environment for data delivery using immune and master–slave swarm cooperative mechanism. The experiment results have illustrated the advantage of heterogeneous WSNs and backup disjoint multipath, and demonstrated the effectiveness, high convergence speed and diversity characteristic of our proposed algorithm. It makes the routing recovery of heterogeneous WSNs more automatic, and can reduce the risk of data delivery loss and energy consumption on the path exploring.

Possible extension of the research may involve studying the routing recovery protocol through a variety of hybridized approaches: merging nature-inspired mechanisms with ABC algorithm [10], incorporation of multi-population model as in multi-population ABC proposed in [5] or migrating population based on co-evolution as in [3]. In addition, the sleep mechanism is another research problem aimed at reducing the energy consumption of the network. One possible future extension can also be on optimizing the combined routing algorithm and the sleep scheduling scheme for lifetime maximization of the WSNs [20], such that our heterogeneous WSNs can be applied more widely.

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References