International Journal of Innovative Computing, Information and Control
Volume **16**, Number **3**, June **2020**

ICIC International ©2020 ISSN 1349-4198
pp. 923–937

RESOURCE ALLOCATION OPTIMIZATION STRATEGY USING IMPROVED DIFFERENTIAL EVOLUTION ALGORITHM IN MULTI-RADIO MULTI-CHANNEL WSNS

Bin Qiu

Department of Computer
Shantou Polytechnic
Donghu, Haojiang District, Shantou 515078, P. R. China
chur8536449@163.com

Received November 2019; revised March 2020

Abstract. *In order to improve the performance of multi-radio and multi-channel wireless sensor networks (WSNs), a resource allocation optimization strategy using improved differential evolution algorithm in multi-radio and multi-channel WSNs is proposed. Firstly, considering the interaction among WSNs node energy consumption, channel allocation, power control and slot allocation, the channel model of multi-node communication and the interference model of the system are constructed. Then, taking the interference and conflict of links as constraints, and taking the objects that reduce energy consumption, increase network capacity and improve the balance of resource allocation as objective functions, a multi-objective optimization model of resource allocation is constructed. The establishment of multi-objective optimization model highlights the trade-off among different objectives. Two-population differential evolution algorithm is employed to solve the model constructed in this paper, and the results are compared with those of standard differential evolution algorithms. The experimental results show that the performance of the network in all aspects has been greatly improved by the use of the proposed algorithm. The simulation results show that the link collisions can be effectively avoided and the network interference is reduced with the utilization of the proposed algorithm. Compared with the existing algorithms, the capacity of key links can be raised by two to three times, and the network capacity and resource allocation balance are improved as a result of application of the proposed algorithm.*
Keywords: Resource allocation optimization, Wireless sensor networks, Multi-radio multi-channel, Improved differential evolution algorithms, Multi-objective optimization model, Slot allocation, Link capacity

1. Introduction.

Wireless sensor network (WSN) is a self-organizing network composed of a group of sensor nodes with sensing, computing and communicating capabilities [1]. It is deployed in the target monitoring area to monitor the environmental conditions of the target area, such as temperature, wind, humidity, and pollution. These sensor nodes coordinate with each other to transfer the perceived data objects to a main location through a self-organizing network. WSN has broad application prospects and attracts much attention in the world. It is considered to be one of the technologies that have great influence on the 21st century. Wireless sensor network is a multi-hop self-organizing network formed by a large number of sensor nodes which communicate with each other in the monitoring areas. With the increasing number of WSNs nodes, the interference of nodes and the communication conflicts between links will also be enhanced, which will not only reduce the network capacity, but also lead to the waste of energy due to data retransmitting of nodes in the network [2]. Therefore, the problem of how to

DOI: 10.24507/ijicic.16.03.923

rationally allocate resources to reduce interference and avoid communication conflicts while increasing network capacity and reducing node energy consumption has to be solved urgently.

In order to improve the performance of multi-radio and multi-channel wireless sensor networks, a joint resource allocation algorithm based on multi-objective optimization model is proposed. Two-population differential evolution algorithm is used to solve the model constructed in this paper, and the results are compared with those of standard differential evolution algorithms. The experimental results show that the algorithm has greatly improved the performance of the network in all aspects. The main innovations are as follows.

1) Considering the interaction among energy consumption, channel allocation, power control and slot allocation of WSNs nodes, the channel model of multi-node communication and the interference model of the system are constructed.

2) With the consumption of WSNs node energy, interference and conflicts are linked as constraints, and with the objective function of reducing energy consumption, increasing network capacity and improving the balance of resource allocation, a multi-objective optimization model of resource allocation is constructed. The establishment of multi-objective optimization model highlights the trade-off among different objectives.

3) Two-population differential evolution algorithm is used to solve the model constructed in this paper, and the results are compared with those of standard differential evolution algorithms. The experimental results show that the algorithm has greatly improved the performance of the network in all aspects.

The chapters of this paper are as follows. Chapter 1 is the introduction, which introduces the background and innovation of this research. Chapter 2 is related work in this field. Chapter 3 introduces the multi-objective optimization model for resource allocation. Chapter 4 is the core of the paper, which introduces the proposed resource allocation optimizing strategy using improved differential evolution algorithms. In Chapter 5, the experiment is designed. Firstly, the parameters of the algorithm are simulated in Matlab environment, and then the algorithm is analyzed through the comparative experiment. Chapter 6 is the conclusion part, which explains the contribution, deficiency and future development direction of this paper.

2. Related Work.

Traditional network resource allocation is carried out separately. Researchers have studied and proposed many multi-radio multi-channel allocation algorithms from the aspects of topology control, channel interference detection, load balancing, link capacity and so on [3]. However, these implementations have some problems, such as low efficiency, poor adaptability or too complex implementation. For example, a separate channel allocation technique was studied in [4]. The network interference could be significantly reduced according to this algorithm. Slot allocation is also a hot issue in current research, which is an effective method to avoid communication link conflicts. However, single channel allocation or slot allocation could only optimize one aspect of the network performance, which kind of optimization may be at the expense of another aspect of the performance. Based on this consideration, many researchers began to devote themselves to the joint optimization of resource allocation. Considering the influence of channel allocation and slot allocation on network performance, a joint optimization algorithm of channel allocation and slot allocation was proposed in [5]. However, this algorithm is just the superposition of the two algorithms mentioned above, which did not really consider optimization. The interaction among them results in a serious waste of resources.

The interaction between channel allocation and slot allocation was taken into account in [6], and the optimized multi-channel allocation mechanism was adopted to achieve slot reuse and channel number optimization. The channel allocation and power control had been jointly optimized and some improvements had been made to the existing work to some extent in [7]. In order to realize the rational allocation of resources, [8] divides the optimization problem into two sub-problems: power allocation and channel allocation. It is proved that the objective function of power control is a convex function, and the optimal transmission power can be obtained in the convex function. [9] studied the general problem of optimal allocation of limited resources in wireless communication networks. Network users are divided into several different groups (or classes) that correspond to different service levels. A channel allocation and power control algorithm based on standard differential evolution was proposed in [10]. However, the limitation of node energy was not considered, nor the interference of possible link conflicts on the network was not considered in this algorithm. The joint congestion control, channel allocation and link scheduling algorithms were proposed for multi-channel, multi-interface and multi-hop wireless sensor networks in [11]. None of the algorithms in the above studies were to study channel allocation, power control and slot allocation jointly. In addition, all the above studies transform the problem to a single-objective optimization problem by weighting method. The results obtained by this method heavily depend on the weights, and the selection of weighting factors can often determine the bias of the results. The problem of how to allocate resources reasonably so as to increase network capacity and reduce node energy consumption while reducing interference and avoiding communication conflicts is still an urgent issue to be solved. Based on this, this paper makes an in-depth study on this issue.

3. **Multi-Objective Optimization Model for Resource Allocation.**

3.1. **Channel model for multi-node communication.** As shown in Figure 1, WSN generally consists of sensor, receiver, sink and data processing center. Sensor nodes are randomly deployed in the target monitoring area, with dozens or hundreds of sensors. These nodes transmit the perceived data along self-organized routes in a hop or multi-hop manner to the sink node, and then the sink node transmits the collected data to the sink node through the Internet or satellite for processing center.

In wireless sensor networks, the main states of nodes are sending, receiving, idling and sleeping. For most nodes, the power consumption of sending state is much greater than

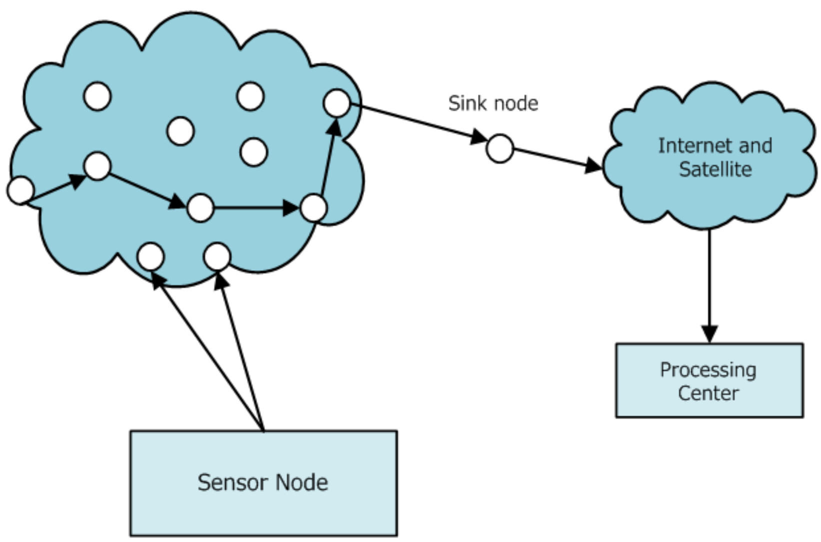

FIGURE 1. Composition of wireless sensor networks

that of other three states. The power consumption of receiving state and idling state is similar, and the power consumption of sleeping state is much less than that of other three states. Therefore, it can effectively reduce the energy consumption of nodes in wireless sensor to make the nodes sleep when the data packets are sent and received accurately.

Figure 2 shows a multi-node communication scenario. In the multi-node scenario, the dynamic characteristics of the interaction between nodes are described by the channel model. Assuming that there are I nodes communicating with the receiving node at the same time, the SIR of the link can be expressed as

$$\Psi^i\left(p_t^1, \ldots, p_t^I\right) = \frac{WA_t^i p_t^i}{R\left(\sum_{j\neq i} A_t^j p_t^j + \sigma^2\right)} \tag{1}$$

W and R represent the bandwidth and transmission rate of the system, p_t^i is the transmission power of node i, A_t^i is the path loss of the corresponding link of the corresponding node i, and $A_t^i = c/(d_i)^4$. σ^2 is thermal noise power. Formula (1) in dB can be rewritten to

$$\Psi^i\left(p_t^1, \ldots, p_t^I\right) dB = 10\log_{10}\left(Wp_t^i/R\right) - \chi^i \tag{2}$$

Among them, $\chi^i = 10\log_{10}\left(\sum_{j\neq i} A_t^j p_t^j + \sigma^2\right)\Big/ A_t^i$ is equivalent to the interference of the corresponding link of node i, and the transmission power of other nodes affects the link quality of node i through χ^i.

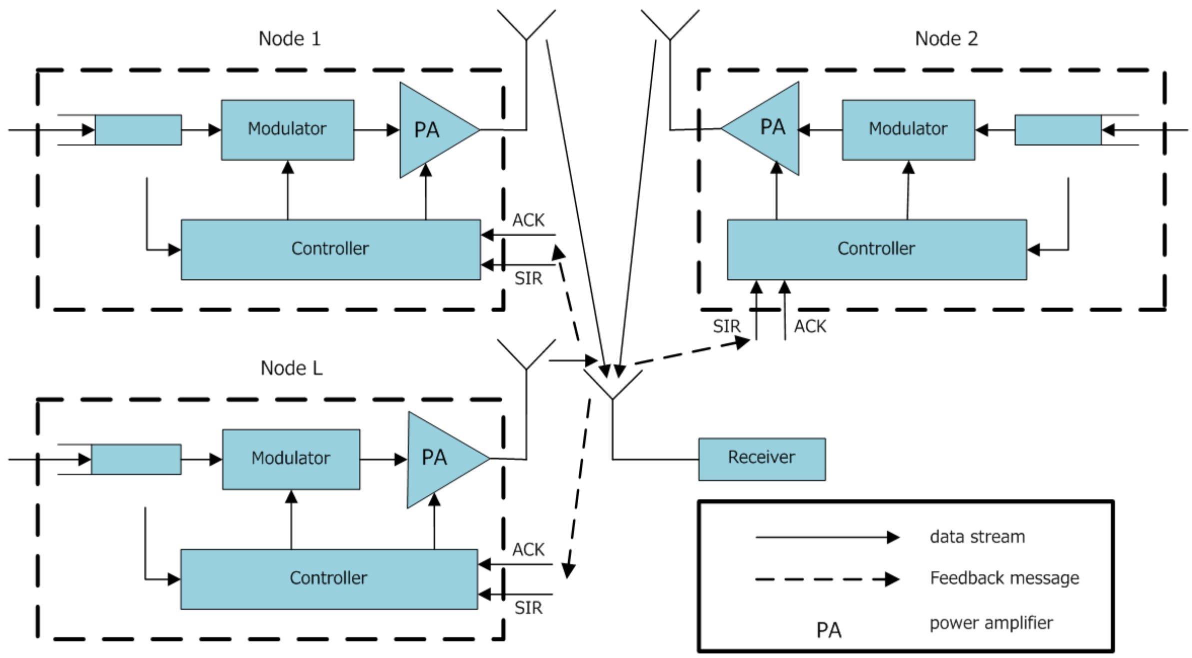

Figure 2. Multi-node communication mode

3.2. **Wireless radio frequency transmission model in links.** Frequency division multiple access (FDMA) is a technique in data communication, in which different users are allocated to channels with the same slots and different frequencies. According to this technology, the frequency bands centrally controlled in the frequency division multiplexing transmission system are allocated to users according to the requirements [12,13]. Compared with fixed allocation system, FDMA enables dynamic switching of channel capacity according to requirements. Through FDMA technology, the available bandwidth is divided into M orthogonal channels with the same bandwidth, and set C is used to represent the orthogonal channel, $C = \{c_1, c_2, \ldots, c_M\}$.

It is assumed that each user device has two sets of independent radio frequency transmitters, which are represented by T_s and R_s respectively. Among them, T_s set is the set of wireless radio frequency transmitters used by users to send data packets, and R_s is the set of wireless radio frequency transmitters used by users to receive data packets. The sets of user nodes T_s and R_s in the link are clearly shown in Figure 3, with parameters set to $|C| = 4$, $|U| = 2$, $k = 3$.

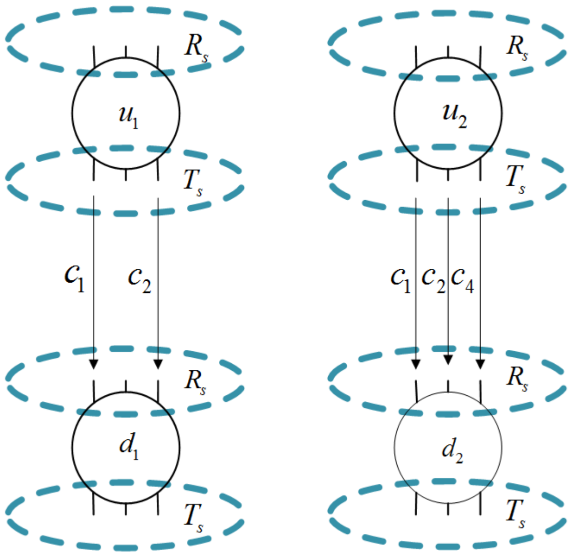

FIGURE 3. Wireless radio frequency transmitter set in link

When two communication users in the same link transmit data, T_s of the sending user and R_s of the receiving user choose the same channel to transmit data. Therefore, only T_s of the sender can be considered, while R_s of the receiving user can be ignored. The user set $U = \{u_1, u_2, \ldots, u_{|N|}\}$ and $k_{u_i,c}$ are defined to indicate the number of radio frequencies used by user u_i on channel c. Since the same channel in different radio frequencies cannot be used by a user to avoid interference, there is $k_{u_i,c} \leq 1$ for any user u_i. In order to improve the utilization of radio spectrum resources and realize the parallel transmission of data over different channels, multi-radio interface is mostly used by the new generation of wireless networks [14-16]. For each radio frequency, at a certain time, it is the only channel to work on. The problem of establishing a network model to achieve channel allocation corresponding to each radio frequency and ensuring wireless network connectivity is the primary issue of channel allocation. At the same time, in a certain range of interference, the ultimate goal of channel allocation is to minimize the interference between radio frequencies and maximize the transmission capacity of wireless networks.

User u_i's strategy is $s_{u_i} = \left(k_{u_i,c_1}, k_{u_i,c_2}, \ldots, k_{u_i,c_{|M|}}\right)$. In the example shown in Figure 3, the policies of users u_1 and u_2 can be expressed as $s_{u_1} = (1, 1, 0, 0)$, $s_{u_2} = (1, 1, 0, 1)$. The policy set of all users can be represented by a matrix $S = \left(s_{u_1}, s_{u_2}, \ldots, s_{u_{|N|}}\right)^T$, and other user policies except user u_i can be represented by s_{u_i}. B_c denotes the total available bandwidth on channel c. Since B_c can be shared equally by the users allocated on the channel, $B_{u_i,c}$ denotes the available bandwidth of user u_i on channel c. The formula is as follows:

$$B_{u_i,c} = B_c \times k_{u_i,c} / k_c \quad \forall u_i \in U, \quad c \in C \tag{3}$$

According to Formula (3), the larger the total number of channel c used, the smaller the available bandwidth $B_{u_i,c}$ and c is used by user u_i on channel c. The utility function of each user u_i is represented by W_{u_i}. In this paper, the user's revenue is set as the user's available bandwidth. Then, the user's revenue function is

$$W_{u_i} = \sum_{c \in C} B_{u_i,c} = \sum_{c \in C} B_c \times k_{u_i,c} \Big/ k_c \tag{4}$$

3.3. **Multi-objective optimization model for resource allocation.** Channel allocation algorithm based on perfect information requires all nodes in wireless network to cooperate globally so that all users can understand the usage of all channels. Because of the selfishness of user nodes in wireless network, it is very difficult to achieve global cooperation [18-20]. Therefore, this algorithm is based on the channel allocation strategy of imperfect information. Each user only knows the usage of all the channels occupied by the user's radio frequency.

In this algorithm, k radio frequencies are allocated to users continuously by distributed way. This allocation step makes the first k channel $c_j \in C$, $j = 1, 2, \ldots, k$ in all channels be used by the radio frequencies of users [21,22]. In order to improve its revenue, the remaining unoccupied channels are redistributed by users through continuous distributed channel allocation. Since each user only knows the channel usage of the channel occupied by the user, the principle of redistribution is to share the number of users of channel c_j used by user u_i (the number of radio frequencies) k_{c_j}. Compared with m_{u_i}, m_{u_i} is the average number of users of channel occupied by user u_i. When $k_{c_j} > m_{u_i}$ is used, the number of users shared by channel c_j is too large, so the free channel $C \backslash c_j$ is allocated to radio frequency of this user.

In order to avoid setting weights, in this paper taking the interference and conflict of links as constraints, and taking the objects that reduce energy consumption, increase network capacity and improve the balance of resource allocation as objective functions, a multi-objective optimization model of resource allocation of the system is constructed, as shown in Formulas (5)-(8).

$$f_1 = \min(\max(z(i))) \tag{5}$$

$$f_2 = \max\left(\sum_{e_{ij} \in E} w_{ij}\right) \tag{6}$$

$$f_3 = \min\left(\sum_{r \in R}\left(W(r) - \frac{\sum_{r \in R} W(r)}{S}\right)^2\right) \quad \text{s.t.} \quad \sum_{l_k \in Link(i)} rl_k - M_i \leq 0, \quad r \in R \tag{7}$$

$$\gamma_{th} - \gamma_{ij} \leq 0 \tag{8}$$

In the above model, Formula (5) denotes the energy consumption of large nodes in minimizing all nodes of the network, and formula $z(i)$ denotes the energy consumption of nodes in a cycle. Assuming that the time length of each slot is t and the number of slots is S, the energy consumption of nodes in a cycle can be expressed as follows:

$$z(i) = \frac{\sum_{e_{ij} \in Net_i(t)} p_{ij} + \sum_{e_{ki} \in Net_i(r)} p_{ki}}{Net_i(t) + Net_i(r)} \tag{9}$$

Here, $Net_i(t)$ represents the link set with node i as the transmitting node and $Net_i(r)$ represents the link set with node i as the receiving node. Formula (6) denotes the enlargement of network capacity. Network capacity reflects the quality of communication to a certain extent. In order to ensure the consistency of the objective function, Formula (6) is transformed into the minimization problem as shown in Formula (10).

$$f_2' = \min\left(-\sum_{e_{ij}\in E} w_{ij}\right) \tag{10}$$

Formula (7) denotes the equalization of the total capacity of all links operating in each slot. If the resource allocation is not balanced, it will lead to the waste of resources, and even the network congestion, resulting in network communication delay [23-25]. In this paper, the balance of resource allocation is expressed by the variance of total capacity in each slot. Here $W(r)$ represents the sum of all link capacities in slot r. Formula (8) denotes interference constraints. In order not to affect normal communication, all links in the network should satisfy the signal-to-noise ratio (SNR) condition, that is, $\gamma_{th} \geq \gamma_{ij}$.

4. **The Proposed Resource Allocation Optimizing Strategy Using Improved Differential Evolution Algorithms.** Differential evolution algorithm is divided into two populations in the iterative process. One is the dominant feasible solution population *popf* which satisfies the interface constraints and interference constraints of all nodes in the network at the same time. The other one is the dominant infeasible solution population *popc*. *popf* also has some memory function. *lbest* is used to remember the optimal solution of each individual in *popf*, and *gbest* is used to remember the optimal solution of *popf* so far. It is an external archive set [26-28]. The main steps of the algorithm include individual coding and population initialization, population variation and crossover, individual selection and population updating [29,30].

4.1. **Individual coding and population initialization.** Since the resource allocation in this paper is based on links, assuming the number of links in the network is L, the dimension of the individual matrix is $3 \times L$. The coding of any individual can be expressed as

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,L-1} & a_{1,L} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,L-1} & b_{2,L} \\ c_{3,1} & c_{3,2} & \cdots & c_{3,L-1} & c_{3,L} \end{bmatrix} \tag{11}$$

When population initialization is carried out, the initial individuals are randomly generated in the optional range of channel, power and time slot. Each individual generated is judged to be feasible according to the node interface constraints and linked interference constraints. The feasible solutions are inserted into population *popf*, and the infeasible solutions are inserted into population *popc*, and the cycle lasts until both *popf* and *popc* are obtained. It satisfies the given population size N_1 and N_2.

4.2. **Variation and crossing of population.** In this paper, the mutation strategy is given to improve the convergence speed of the algorithm by learning from the better individuals.

$$Q(r1) = popf(r1) + F(lbest(r2)) - popf(r3) + F(gbest(r4)) - popf(r5) \tag{12}$$

Among them, $Q(r1)$ corresponds to the experimental individual produced by mutation operation of the $r1$ resource allocation scheme individual in *popf*, while the other $r2$, $r3$, $r4$, $r5$ are randomly selected from the corresponding set of individuals with differences. The crossover operation in the algorithm adopts a uniform crossover mode. Each column of the individual matrix of the resource allocation scheme is regarded as a crossover point, that is, each link is a crossover point. As shown in Formula (13), P_j is a random number in the interval $[0, 1]$ generated by column H in the experimental individual $Q(r1)$, and j is a given parameter.

$$G(r1)_j = \begin{cases} popf(r1)_j, & P_j > Cr \\ Q(r1)_j, & \text{others} \end{cases} \tag{13}$$

The variable range of experimental individual $G(r1)$ may exceed the optional range of channel, power and time slot specified in this paper. At this time, the unconstrained elements in $G(r1)$ need to be treated by boundary conditions, and the treated individuals are recorded as $son(r1)$.

4.3. **Individual selection and population renewal.** Firstly, the feasibility of individuals in progeny *son* was judged, and feasible solutions and infeasible solutions were inserted into *popf* and *popc* respectively. Then, the dominant relationship between any two individuals in *popf* and *popc* is judged, the dominant individuals are deleted, and the judgement is stopped when the population size reaches N_1 and N_2. If the population size is still larger than N_1 and N_2 after deleting all the dominant individuals, then the crowding degree of the individual is calculated and the individuals with small crowding degree are deleted to ensure that the population size does not change.

4.4. **Best equilibrium solution.** In order to select a good equilibrium solution from the Pareto solution set, a linear membership function for each objective function (f_i) is defined in this paper, as shown in Formula (14), where $i = 1, 2, 3$ substitutes each dominant solution (g) in set *gbest* into the objective function (f_i), and the corresponding large value ($f_i^{\max}$) and small value ($f_i^{\min}$) of the objective function (f_i) can be obtained.

$$u_i = \frac{f_i - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \tag{14}$$

From Formula (14), it can be seen that the smaller the value of membership function corresponding to the individual of the dominant solution, the stronger the degree of realization of the objective function. For each dominant solution (g) in *gbest*, the aggregation degree function is defined as shown in Formula (15). The aggregation degree function represents the sum of membership degrees of all objective functions corresponding to dominant solution (g), where m represents the number of objective functions, and $m = 3$ is used in this paper.

$$\Gamma^g = \sum_{i=1}^{m} u_i^g \tag{15}$$

Formula (15) shows that the individual with small aggregation degree function is the good equilibrium solution required in this paper.

4.5. **Algorithm steps.** In summary, the algorithm steps are summarized as follows.

Step 1. Set the initial values of the mutation factor F, the cross probability C_r, the number of iterations $m_{\max}$, the feasible solution population size $N1$, and the infeasible solution population size $N2$. Generate the initial populations *popf* and *popc* and initialize *lbest* and *gbest* as described in Section 4.1.

Step 2. The individual in *popf* generates the experimental population G after the mutation operation of strategy 1 or strategy 2 and the crossover operation shown in Formula (13).

Step 3. Out-of-range elements in experimental population G are processed by boundary conditions to produce offspring population *son*.

Step 4. Judge the feasibility of individuals in *son*, insert feasible solutions into *popf* and *gbest*, and insert infeasible solutions into *popc*.

Step 5. Update *popf* and *popc* as described in Section 4.3.

Step 6. Update *lbest* based on feasibility and dominance. If $son(r1)$ is a feasible solution, determine whether $son(r1)$ is dominated by $lbest(r1)$. If $son(r1)$ dominates the corresponding individual $lbest(r1)$, then replace $lbest(r1)$ with $son(r1)$, otherwise, it is not replaced; if $son(r1)$ is an infeasible solution, $lbest(r1)$ is not updated and *gbest* is updated. $m = m + 1$.

Step 7. Determine whether $m \leq m_{\max}$ is true. If yes, go to Step 2. Otherwise, go to Step 8.

Step 8. Output the optimal solution set *gbest*.

Step 9. An optimal equilibrium solution is selected according to the linear membership function and the aggregation function.

5. Simulation Results and Analysis.

5.1. Simulation settings.
In this section, the parameters of the algorithm are simulated under the environment of MATLAB, and then the algorithm is analyzed through comparative experiments. In order to select the suitable mutation factor and crossover probability, the simulation experiments of mutation factor F and crossover probability C_r are carried out. The known network topology is shown in Figure 4. Figure 4 denotes the node number. The given number of nodes is 25 and the number of links is 24. The arrow represents the one-way link of communication between nodes. Other parameter settings are shown in Table 1.

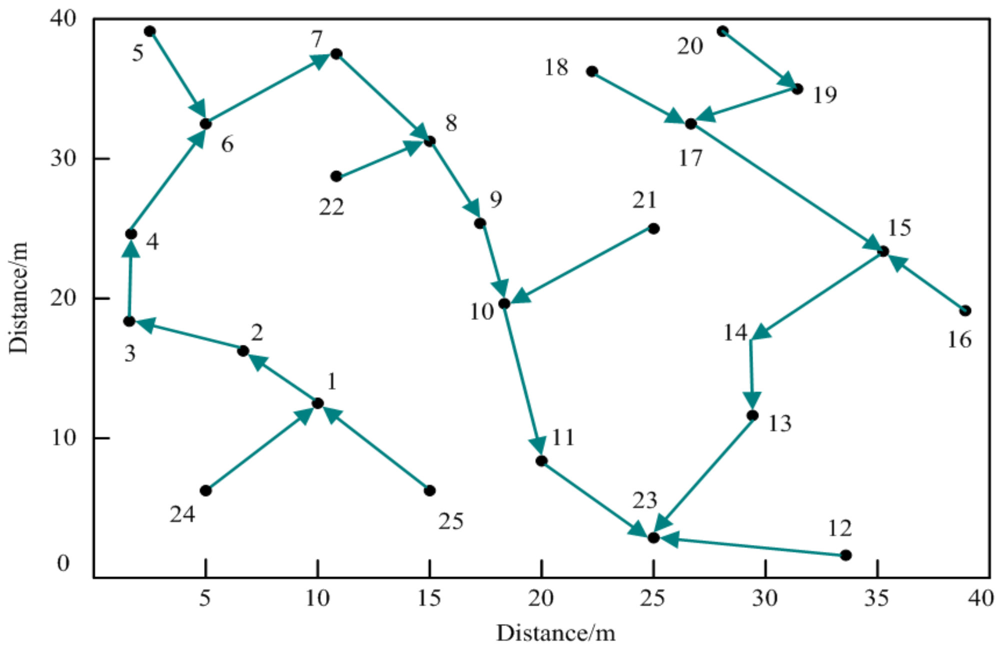

FIGURE 4. Network topology

5.2. Performance comparison with standard differential evolution algorithm (DE).

5.2.1. *Comparison of channel allocation and slot allocation results.* The joint allocation of power control and channel allocation is studied based on standard differential evolution [14]. In order to verify the performance of the proposed algorithm, the proposed algorithm is compared with the DE-based resource allocation algorithm, and the number of iterations

TABLE 1. Setting of simulation parameters

Parameter	Value
Maximum power $p_{\max}/\mathrm{W}$	0.15
Number of node interfaces	2
Channel width H_m/Hz	20
Time length of each slot t/s	1
White noise N_0/W	1×10^{-7}
Drying ratio γ_{th}/dB	3.6
Number of iterations	2000
Number of available channels	5

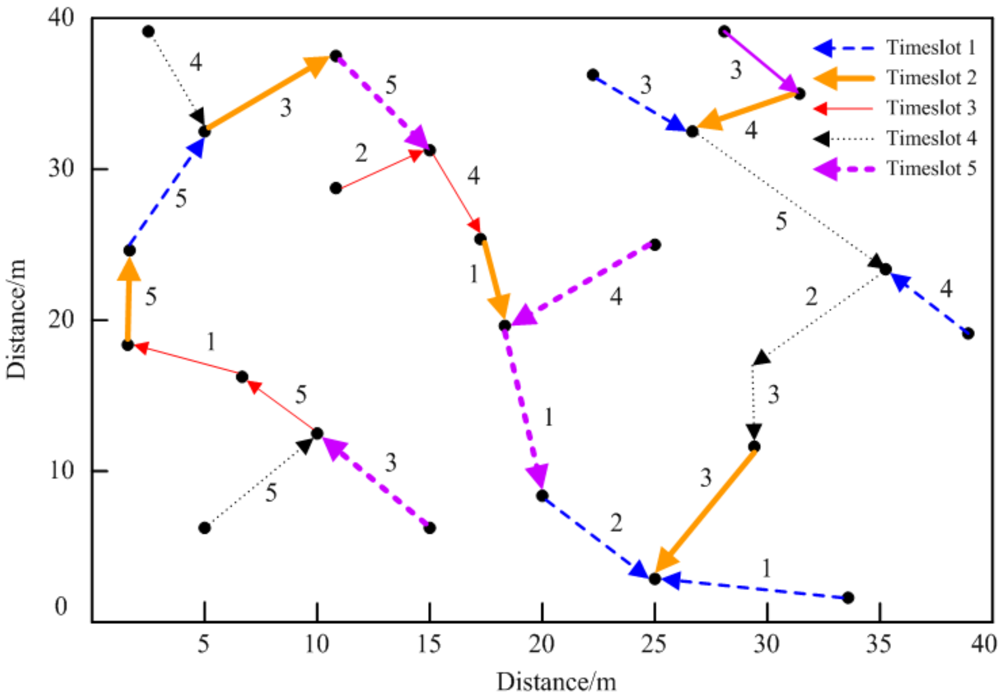

FIGURE 5. Channel allocation and slot allocation results

is set to 2000, resulting in channel allocation and slot allocation. The results are shown in Figure 5 and the load balance in each slot is shown in Figure 6.

Figure 5 and Figure 6 respectively show the final results of the algorithm. In Figure 5, links in different slots are marked with different symbols, while the numbers on the links represent the channels used for the link communication. As can be seen from Figure 7, the results obtained show that the communication conflicts of the links are effectively avoided, and finally the numbers of slots are used in the whole network. The numbers of links in each slot are 5, 5, 4, 5 and 5, and the numbers of links in each channel are 4, 3, 6, 5 and 6. Combined with Figure 6, the balance of resource allocation can be better reflected.

5.2.2. *Comparison of link interference, channel average interference and network capacity.* The comparison of link interference, average channel interference and network capacity is shown in Figures 7 and 8, respectively. From Figure 7, we can see that the proposed improved differential evolution algorithm makes the interference of links more balanced and close to zero. Because the standard differential evolution algorithm does not consider

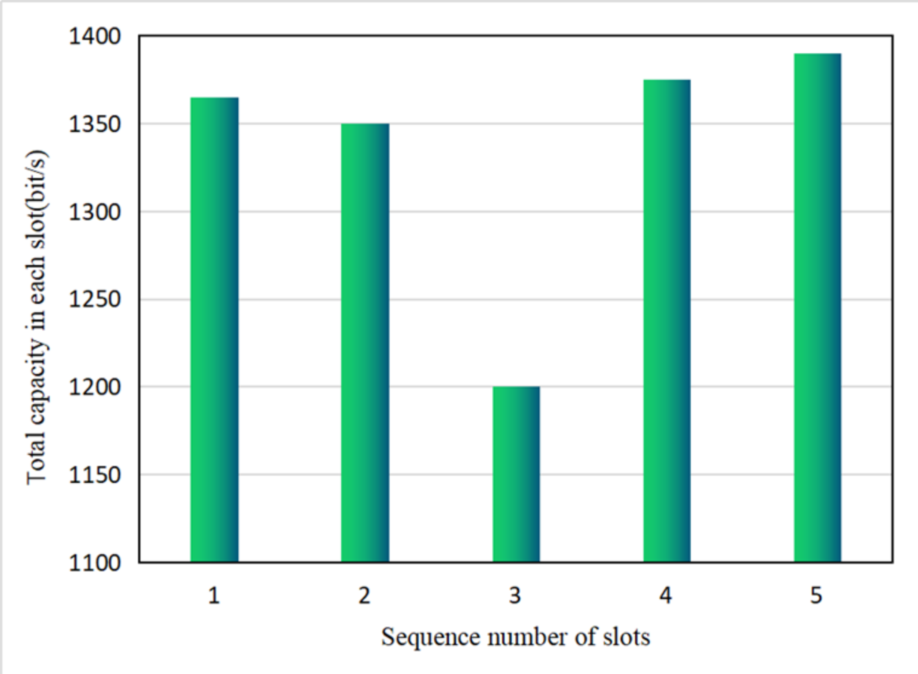

FIGURE 6. Load balancing for each slot

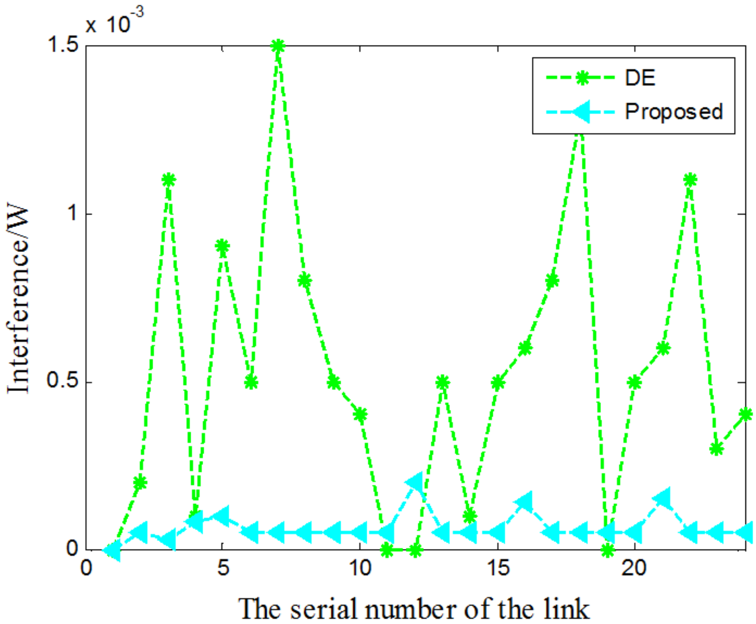

FIGURE 7. Link interference

the influence of time slot on interference, the interference obtained by the standard differential evolution algorithm is larger than that of the proposed improved algorithm, and the standard differential evolution algorithm is used. Similarly, the average interference in each channel in Table 2 shows that the improved algorithm has stronger anti-jamming ability.

From Figure 7, it can be seen that the link interference of the improved algorithm is less than that of DE, so the network capacity of the proposed algorithm is much larger than that of the standard differential evolution algorithm.

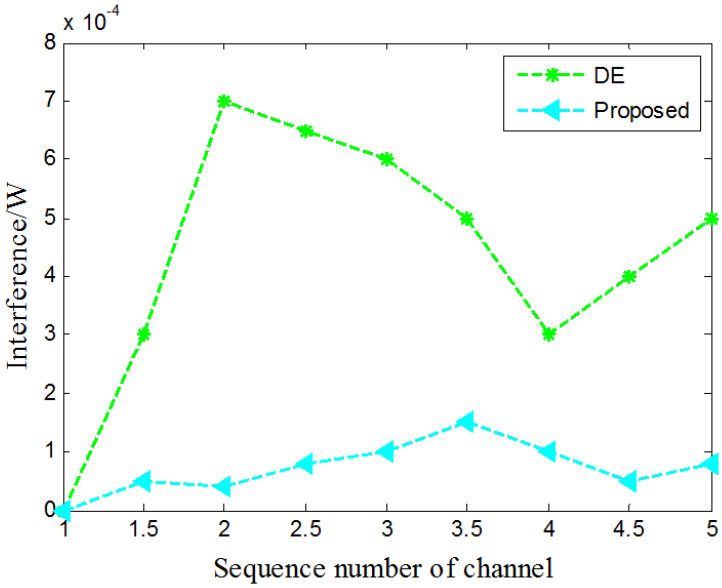

FIGURE 8. Average interference of each signal

TABLE 2. Comparison of network capacity between two methods (bit$\cdot$s^{-1})

Method	**20**	**25**	**30**	**35**	**40**
Proposed	5025	6834	7358	8214	10025
DE	3018	4016	5216	5615	6126

5.3. **Performance comparison with current advanced algorithms.** A static wireless network with a fixed number of nodes are randomly distributed in the range of 500 m. 500 m in the scene is configured, in which a node is randomly selected as the gateway node, and the traffic from the gateway to the wired network is assumed to be unrestricted. Each node is configured with three radio frequencies based on IEEE802.1la standard. The radio frequencies can use 12 non-overlapping channels, assuming that the maximum transmission capacity is 54 Mbps. In the network, nodes are randomly selected as service sources to generate services. The traffic of each service source is 1 Mbps and it can be repeated and accumulated on the same node. Multi-path routing algorithm is used in the algorithm simulation. Under the same network topology, three other commonly used multi-radio multi-channel allocation algorithms are simulated to compare the performance of the three algorithms.

Figure 9 shows how the key of network link capacity changes under different channel allocation schemes when different traffic flows are configured. As can be seen from the graph, compared with the algorithms in [4,5], the proposed algorithm can guarantee high link capacity at key links. When the traffic is small, the probability of simultaneous use of the same frequency link is small, and the actual link capacity of the key link is high. With the increasing of traffic, the probability of simultaneous use of co-frequency links in the link interference domain increases, and the inherent capacity of co-frequency link equalization link channel increases as well. The change in the actual capacity of key links in the figure reflects this situation. After the traffic changes to 5 Mbps, the capacity of key links does not be changed significantly with the traffic increasing, which indicates that the same frequency links in the interference domain of key links are mostly in the traffic transmission state.

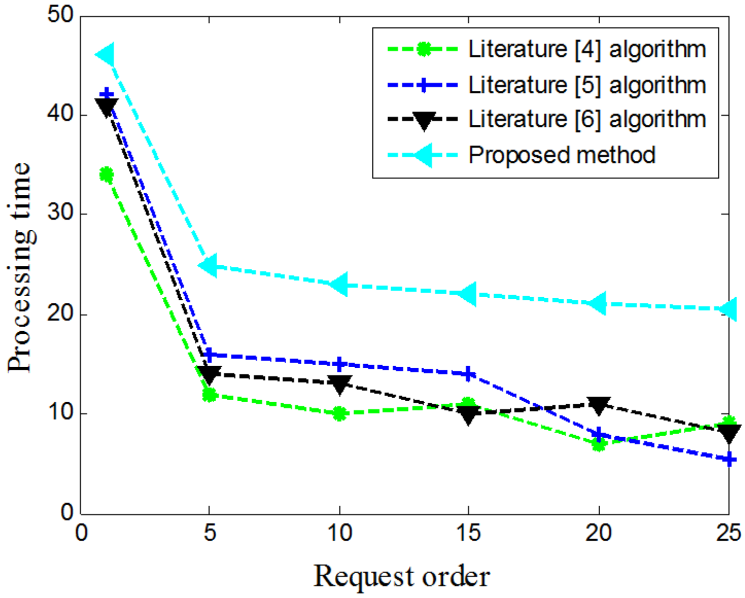

FIGURE 9. The change of network's key link capacity under different channel allocation schemes

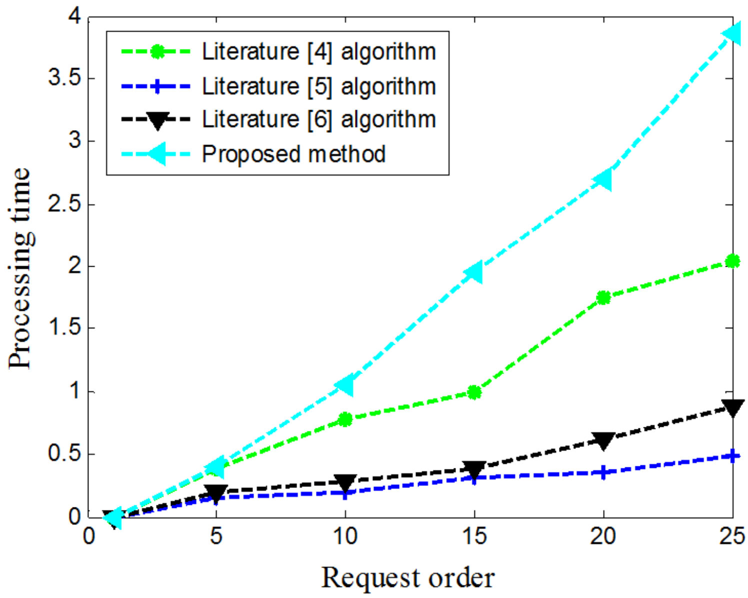

FIGURE 10. The change of the load capacity ratio of key links under three different channel allocation schemes

Figure 10 shows the change of the load capacity ratio of key links under three different channel allocation schemes when configuring different traffic flows, which reflects the satisfaction of link capacity to network traffic requirements. As can be seen from the graph, with the increase of traffic, the link capacity generated under the algorithm proposed in [6] cannot meet the network traffic requirements very quickly. Under 10 Mbps traffic, the ratio of the link demands capacity and the actual capacity generated by [6] algorithm is close to 1, and the key link capacity cannot meet the transmission requirements of network services. The channel allocation results generated by this algorithm show that the capacity requirements of critical links for network services can be well met even under the maximum network traffic of 25 Mbps.

The allocation results of the channel allocation algorithm in this paper show that the high link capacity of the key links can be ensured, which is two to three times as much as that of the two other algorithms. By means of this algorithm, the capacity on the key links is improved, the bottleneck of network transmission is solved, and the capacity of wireless network is improved. The network can meet the larger demand of service transmission. At the same time, the recovery mechanism of the network after node failure ensures the network connectivity and long-term stable operation.

6. **Conclusion.** In this paper, the relationship among energy consumption, channel allocation, power control and slot allocation of WSN nodes is considered synthetically. With the link conflict and interference as constraints, the objective function is to reduce network energy consumption, maximize network capacity and improve the balance of resource allocation. A multi-objective optimization model of resource allocation is constructed. Considering the complexity of solving the multi-objective optimization problem, the double group differential evolution algorithm is used to solve the model iteratively.

In the case of increasing network traffic, compared with the existing common algorithms, the algorithm in this paper can improve the capacity of key links 2 to 3 times, which is an effective channel allocation algorithm. The algorithm improves the capacity of key links, solves the bottleneck of network transmission, and improves the capacity of wireless network. The network can meet the needs of large business transmission. At the same time, the recovery mechanism of the network after node failure ensures the connectivity and long-term stable operation of the network. The disadvantage of this channel allocation algorithm is that it does not realize the real-time adjustment of channel allocation. Dynamic channel allocation based on network condition will be the next research direction.

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