

# Research Article

# Hybrid Niche Immune Genetic Algorithm for Fault Detection Coverage in Industry Wireless Sensor Network

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The industry wireless sensor network (IWSN) technology, which is used to monitor industrial equipment, has attracted more and more attention in recent years. Sensor nodes in IWSN can spontaneously complete distributed networking and carry out monitoring tasks under random deployment conditions. Therefore, a self-organized IWSN is particularly suitable for the fault detection and diagnosis of industrial equipment in complex environments. However, due to the detection, ability of a single sensor node is limited, and the monitoring distribution problem is a typical multidimensional discrete NP-hard combinatorial stochastic optimization problem, which is challenging to solve for the traditional mathematical methods. With the purpose of improving the target monitoring capability and prolonging lifetime of IWSN, a novel hybrid niche immune genetic algorithm (HNIGA) for optimizing the target coverage model of fault detection is proposed. It uses the genetic operation to evolve antibody groups and applies niche technology to maintain the diversity of antibody groups. As a result, HNIGA can effectively reduce the failure rate of detection targets. To verify the performance of HNIGA, a series of simulations under different simulation conditions are carried out. Specifically, HNIGA is compared with genetic algorithm (GA) and simulated annealing (SA). Simulation results show that HNIGA has a faster convergence speed and more robust global search capability than the other two algorithms.

## 1. Introduction

With the rapid development of the manufacturing industry, machine fault diagnosis plays an increasingly important role in ensuring the safe operation of equipment [1–3]. Unexpected equipment failures will cause severe damage to the equipment and cause more economic losses due to the interruption of plant operation. Therefore, a lot of fault diagnosis research works are proposed to focus on effective maintenance procedures.

Industrial wireless sensor network (IWSN) provides an effective scheme for machine fault diagnosis [4]. More specifically, IWSN is a distributed wireless network that transmits node information to users by monitoring, sensing, and processing node data through multiple sensor nodes [5–7]. Besides, various microsensors are integrated on each node, effectively collecting and monitoring different physical data such as temperature, humidity, acoustic parameters, and optical parameters. These pieces of information are transmit-

ted to the sink node using wireless links in a multihop selforganizing manner. Then, they are sent to the monitoring center through GPRS, satellite, microwave communication, or the Internet. Subsequently, users can collect the information of interest or further control other nodes' actions on the network through the aggregation node. IWSN is usually deployed in harsh environments without infrastructure and unattended [8]. Due to their unique advantages of rapid deployment, survivability, high concealment, and low cost, IWSN is widely used in many fields.

An essential part of the IWSN applied to the fault detection and diagnosis of industrial machines is to improve the coverage rate of monitoring points [9]. Coverage control is a fundamental problem in IWSN, and it is also a measurement standard of quality of service (QoS) evaluation in IWSN. The IWSN coverage reflects the monitoring quality of the target area by the IWSN and provides the sensing services required by the system [10, 11]. An effective IWSN coverage control strategy can optimize the resource allocation of the network, improve the energy efficiency of network nodes, and perceive the quality of service.

In engineering practice, to obtain data from the entire area, coverage is one of the most basic requirements. In many cases, wireless sensor networks require monitoring various areas of the network to fully cover the monitored targets. However, in some other wireless sensor network applications, a specific percentage of the network needs to be monitored [12]. Generally speaking, coverage problems can be classified into three categories according to the coverage object: target, area, and barrier coverage [13, 14]. Point coverage refers to the random deployment of sensor nodes near some discrete target points in a given area for data collection and monitoring. The point coverage problem is usually studied by selecting some of the sensor nodes randomly deployed in the area to monitor a specific point in anticipation of the location of the monitored point, optimizing the application of network resources, and ensuring the completion of the monitoring task. Given a fixed target area, the sensor node can monitor all the subareas under that target area is the area coverage, which is aimed at achieving the maximum coverage of the target area. Barrier coverage means that the sensing range of the working node should cover the whole moving trajectory of the moving object when it traverses the area along a specific track. Its purpose is to identify any intruder who may try to enter the network area. This identification helps prevent intruders from sneaking through the network [15].

In the industrial wireless sensor deployment process, two strategies are generally used: random deployment and planned deployment. Because IWSNs typically operate in complex environments and have many industrial wireless sensor nodes in the network, random deployment is often used. However, it is difficult to deploy all industrial wireless sensor nodes to the correct location at the same time by large-scale random deployment method, which is easy to generate unreasonable coverage structure, and form perceptual overlap and blind spot. In this case, the redundant deployment of sensor nodes compensates for the low sensor coverage. Besides, suppose there is an appropriate scheduling mechanism to schedule the activities of sensor nodes. In that case, it will significantly improve the coverage of sensors in IWSN and extend the lifetime of IWSN [16].

To obtain the maximum monitoring range and prolong the lifetime of IWSN with a limited number of nodes, this paper proposes a self-organizing IWSN target coverage method based on a hybrid niche immune genetic algorithm (HNIGA) and establishes a corresponding system model. HNIGA uses genetic operation to evolve antibody populations and niche technology to maintain the diversity of antibody populations, thereby increasing the diversity of the population and increasing the coverage of the target. In the simulations, HNIGA is compared with SA and GA. Simulation results show that the number of target coverage optimized by HNIGA has increased significantly. And considering the quality of service of the network, more rounds of monitoring can be carried out on the target points after the optimization of HNIGA, which means that the monitoring life of the whole network is effectively extended.

The structure of this paper is as follows. Section 2 introduces related research work on target coverage in IWSN, and Section 3 establishes the fault detection coverage model in detail. HNIGA is used to improve the performance of the monitoring capability of IWSN in Section 4. Section 5 shows and discusses the results of the simulation experiment of HNIGA. Then, Section 6 provides a comprehensive summary.

#### 2. Related Work

To maximize capital productivity, reduce health, safety, and environmental (HSE) risks and minimize costs. Paper [17] proposes to collect, process, and analyze data from the device in real time with the help of IWSN through the Internet of Things technology. Paper [18] stated that if detailed machine health indicators are to be analyzed, the infrastructure should accommodate data from sources other than the machine controller itself. The paper proposes a digital architecture that meets these standards and demonstrates use cases in machine utilization and health monitoring to achieve this goal. Paper [19] proposes a hierarchical routing graph construction (HRGC) to meet the needs of real-time and reliable communication in IWSN. In IWSN, quality of service (QOS) is expressed as the accuracy with which the sensor covers or monitors the target set within its sensing range.

In paper [12], which is aimed at the problem of connected p-persistent coverage in wireless sensor networks (WSNs), they proposed a pDCDS algorithm, which is based on the connected dominating set of degree constraints, can significantly improve the network lifetime. In paper [15], a distributed boundary monitoring (DBS) algorithm is proposed, which can find the best node to ensure obstacle coverage. Paper [16] proposes an efficient scheduling method LAML based on learning automata. The algorithm makes nodes choose their appropriate state (active or sleeping) at any given time to extend the lifetime of the network better.

The key to using IWSN to monitor industrial equipment is to maximize the number of monitoring points under a limited number of industry wireless sensors while considering the energy limitation of the wireless sensor itself. When each target needs to be covered by a fixed number of sensors, the sensor nodes need to be dynamically adjusted to monitor deployment targets to improve detection efficiency. Researchers have done much work on the target coverage problem in IWSN and put forward many solutions.

Paper [20] designs a model based on hybrid optimization to solve the coverage and connection problems. An optimization method based on Hybrid Film Group Optimizer (TSO) is proposed to optimize the problem. Paper [21] points out that a critical issue in industrial wireless sensor networks is coverage. In that paper, an energy-efficient heuristic method is used to solve the k-coverage problem. The experimental results show that the performance of the heuristic algorithm is close to the best and shows an improvement in network lifetime. However, because the implementation of the solution is too complicated, it is not suitable for actual operation.

Paper [22] proposes an adaptive coverage and connectivity (ACC) scheme. It uses two basic methods, the first of which can provide the best coverage for all target objects,



FIGURE 1: Fault diagnosis of industrial equipment in IWSN.

and its mathematical model can ensure coverage. The second method deals with network connectivity and energy consumption. Paper [23] divides the deployment set of all sensors into disjoint subsets or sensor coverings so that each sensor covering can monitor the entire target at any time. Then, a cuckoo search algorithm is proposed to optimize the sensor coverage problem to achieve the goal of maximizing the coverage of target points. However, the cuckoo algorithm has the problem of weak local search ability and slow convergence speed, and it cannot search for the optimal solution in a short time.

Paper [24] proposes an improved wireless sensor network scheduling based on genetic algorithm. An effective chromosome representation is given, and it is proved that it produces effective chromosomes after crossover and mutation operations. The derivation of the fitness function has four contradictory goals, choosing the least number of sensors, the full coverage of the selected sensor nodes, connectivity, and energy level. In that paper, a novel mutation operation is introduced to improve the performance of GAbased algorithms and speed up the convergence speed. However, GA has a specific dependence on selecting the initial population, which makes the algorithm prone to premature maturity and premature convergence.

Paper [25] uses SA and PSO to deploy sensor nodes effectively and determine the sensing range of sensor nodes in advance. Then, SA and Dempster-Shafer theory are used to effectively schedule the sensor nodes, thereby finding the optimal scheduling scheme and location of the sensor nodes. However, due to the requirement of higher initial temperature, slower cooling rate, lower final temperature, and enough sampling at each temperature, the optimization process is longer, and the convergence speed is slow. Thus, it is not easy to achieve the ideal optimization effect in a short time.

#### 3. System Model

3.1. Problem Description. In industrial equipment monitoring, industry wireless sensors need to be used to monitor target points. Under the condition of limited resources, the sensor monitoring scheme optimized by HNIGA can maxi-

mize the number of monitored target points and improve the monitoring efficiency of IWSN. It can be better applied to the condition monitoring of industrial production equipment to avoid unnecessary losses. As in Figure 1, the industry wireless sensor nodes are arranged on industrial equipment. Each diagnostic node is an intelligent industry wireless sensor that can collect various signals generated by the operation equipment. According to the different data types that need to be collected, industry wireless sensors are divided into vibration sensors, flow sensors, and temperature sensors. These intelligent industry wireless sensors have specific data processing capabilities and can convert collected analog data into digital signals. Second, the industry wireless sensors send the collected data to the receiving device in a specific format through IWSN. The receiving device can convert the data collected from the sensors into computer-recognizable data and then submit it to the service terminal. The service terminal processes the collected data, and it can also actively send requests to the equipment for obtaining specified types of data. The service terminal records the collected or requested data, analyzes current or historical data according to specific diagnostic algorithms, evaluates the current equipment operation state or predicts the subsequent operating state of the equipment, and provides maintenance and diagnosis recommendations.

Lifetime analysis is an essential issue in IWSN design. The purpose of lifetime analysis is to extend network life as long as possible. Hence, network designers need to optimize network design from different perspectives to extend the lifetime of IWSN. There are three main methods commonly used to define the network lifetime, the definition based on the number of effective nodes, the lifetime definition based on the coverage, and the lifetime definition based on the connectivity.

However, in this paper, the definition of lifetime is based on the quality of service (QoS). The fundamental purpose of the network is to serve the fault diagnosis of industrial equipment in IWSN. If the network cannot meet the requirements, the network will be invalid. Thus, in the simulation, the network lifetime is defined as follows. The energy of sensor nodes shows a normal distribution. When the target coverage



FIGURE 2: Coverage relationship between sensors and targets.

in the network is less than 50%, the whole monitoring network will stop working. The working life of the network is defined as the total working time.

To achieve monitoring goals, the IWSN must form a complete monitoring area coverage and meet the coverage requirements of certain applications.

3.2. Target Coverage Model. In the process of monitoring target points using IWSN, each industry wireless sensor node can monitor multiple target points within its sensing radius, and one target point can also be monitored by multiple industry wireless sensor nodes around it. Moreover, the cooperation of multiple industry sensor nodes can improve the accuracy of monitoring data.

To obtain accurate location information of the monitored target point, at least three industry wireless sensors are required to monitor the target point at the same time successfully. As shown in Figure 2, the black dots represent the industry wireless sensors, the circle represents the area that the sensor can monitor, and the four-pointed star is the target point to be monitored. Only when the target point is in the overlap area of the 3 industry wireless sensor monitoring ranges, the accurate position of the target point can be successfully obtained, which is beneficial to diagnosing and maintaining the target point.

Assuming that M industry wireless sensor nodes and N target points are placed in a monitoring area with a range of  $L \times L$ , in this paper, the value of L is 400 meters, and the coverage relationship between monitored target points and industry wireless sensor nodes is expressed by formula (1).

$$C = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,N-1} & c_{1,N} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,N-1} & c_{2,N} \\ \vdots & c_{m,n} & \vdots \\ c_{M-1,1} & c_{M-1,2} & \cdots & c_{M-1,N-1} & c_{M-1,N} \\ c_{M,1} & c_{M,2} & \cdots & c_{M,N-1} & c_{M,N} \end{bmatrix}$$
(1)  
$$\cdot (c_{m,n} \in \{0, 1\}, 1 \le m \le M, 1 \le n \le N).$$

Due to the limitation of industry wireless sensor monitoring capabilities, the industry wireless sensor nodes can only select a limited number of monitored target points within their monitoring area for monitoring. The monitoring relationship between industry wireless sensor nodes and monitored target points in IWSN can be shown in formula (2).

$$S = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,N-1} & s_{1,N} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,N-1} & s_{2,N} \\ \vdots & \vdots & s_{m,n} & \vdots & \vdots \\ s_{M-1,1} & s_{M-1,2} & \cdots & s_{M-1,N-1} & s_{M-1,N} \\ s_{M,1} & s_{M,2} & \cdots & s_{M,N-1} & s_{M,N} \end{bmatrix}$$
(2)  
$$: (s_{m,n} \in \{0,1\}, 1 \le m \le M, 1 \le n \le N).$$

In the monitoring relationship matrix *S*, when  $s_{m,n} = 1$ , it shows that the  $n^{\text{th}}$  sensor node is used to monitor  $m^{\text{th}}$  target point, and if  $s_{m,n} = 0$ , it means that although the  $m^{\text{th}}$  target can be sensed by the  $n^{\text{th}}$  node, but it is not monitored by  $m^{\text{th}}$  sensor node at this time. Considering the energy limitation of industry wireless sensor, each sensor can only monitor at most *F* target points, and the restrictions can be described as formula (3).

$$\sum_{n=1}^{M} s_{m,n} \le F, n = 1 \cdots N.$$
(3)

Each industry wireless sensor node can monitor at most F targets simultaneously, since the information of the monitored target point needs to be accurately obtained. To obtain the maximum number of targets that are detected by the sensor, the objective function is designed as formula (4).

$$\sum_{m=1}^{M} s_{m,n} \le F, n = 1 \cdots N.$$

$$\tag{4}$$

Each industry wireless sensor node can monitor at most F targets simultaneously, since the information of the monitored target point needs to be accurately obtained. To obtain the maximum number of targets that are detected by the sensor, the objective function is designed as formula (5).

$$\max f(s_{11}, s_{12}, \dots, s_{MN}) = \sum_{m=1}^{M} w_m,$$
(5)



FIGURE 3: Algorithm flowchart.

where the objective function f denotes the number of targets successfully monitored when the monitoring matrix is R, and  $w_m$  is described as formula (6).

$$w_{m} = \begin{cases} 1 & \sum_{n=1}^{N} s_{m,n} \ge E, \\ 0 & \sum_{n=1}^{N} s_{m,n} < E. \end{cases}$$
(6)

The restrictions are described as formulas (7) and (8).

$$\sum_{m=1}^{M} s_{m,n} \le F, n = 1 \cdots N,$$

$$\tag{7}$$

$$s_{m,n} \le c_{m,n}.\tag{8}$$

Equation (7) indicates that each node can simultaneously monitor F objects at most, and formula (8) represents that a target can be monitored by a sensor node only if it is within the node coverage.

In this paper, fault detection coverage is a kind of point coverage described as the industrial wireless sensors are randomly deployed in a designated monitoring area to continuously monitor the key points of industrial equipment in this area. The monitoring effect of the network is expressed by the target coverage, which refers to the proportion of the number of successfully detected target points in the total number of target points. To exclude the emergence of a single special case, the network coverage under the same condition is calculated 10 times, and then, the average value is taken as the final network coverage.

## 4. HNIGA-Based Fault Detection Coverage in IWSN

In this paper, a novel optimization algorithm HNIGA is used to solve the problem of fault detection coverage in IWSN, which follows the framework of conventional heuristic methods and is a randomized search algorithm that draws on natural selection and natural genetic mechanisms of the biological world. The algorithm uses niche technology to maintain the diversity of solutions. It has a high global optimization capability and convergence speed simultaneously. It overcomes two typical disadvantages of traditional genetic algorithms: GA is prone to premature, which makes the final search results in the local optimal solution. In the later stage of GA evolution, the search efficiency will decrease, and the search speed will slow down.

In HNIGA, the antigen is considered as a problem, and the antibody corresponds to the candidate solution of the problem. This paper introduces the niche technology based on the crowding-out mechanism, which can avoid the large number of antibodies with high affinity in the later stage of the algorithm evolution, filling the entire group. It can better maintain the diversity of solutions and has a high global optimization capability and convergence speed. The basic idea is

A	1	0	0	1	1	1	0	0	crossover	A'	1	0	0	1	1	1	1	1
В	1	1	0	0	0	1	1	1		B'	1	1	0	0	0	1	0	0
A	1	0	0	1	1	1	0	0	Double-point crossover	A'	1	0	0	0	0	1	0	0
В	1	1	0	0	0	1	1	1		B'	1	1	0	1	1	1	1	1
									_									
A	1	0	0	1	1	1	0	0	Multi-point crossover	A'	1	0	0	0	0	1	1	0
В	1	1	0	0	0	1	1	1		B'	1	1	0	1	1	1	0	1

FIGURE 4: Cross operation diagram.

to set a crowding factor CF in the algorithm and randomly select 1/CF individuals from the group to form exclusion members. Then, with the similarity between the newly generated antibodies and the excluded members, some antibodies similar to the excluded members are excluded. The similarity between antibodies can be measured by the Hamming distance between the antibody code strings. New individuals always replace the antibodies close to them, which can prevent the population from converging to an only antibody to a certain extent. As the crowding process proceeds, the antibodies in the group are gradually classified, thus forming a small generation environment and maintaining the diversity of the group.

HNIGA uses a two-dimensional matrix to represent antibodies, and each antibody denotes a solution for target coverage. HNIGA's algorithm flow is as follows.

*Step 1.* Determine the evolutionary algebra and then initialize an antibody population using chaos operator.

*Step 2.* Apply the sharing mechanism algorithm to the initial population to obtain the memory antibody set.

Step 3. A certain number of antibodies with higher affinity are selected from the initial population to form a new population to be evolved. The sum of the number of this population and the number of memory antibody sets is the number of the initial antibody population.

*Step 4.* Evolve the new antibody population generated in Step 3 by selecting cross and mutation operations.

*Step 5.* Combine the evolved new antibody population with the memory antibody set to form a new antibody population and select a new memory antibody set from the population.

*Step 6.* Randomly generate some new antibodies and form a new antibody population with the memory antibody set, the size of which is the same as the initial population.

*Step 7.* Judge whether the termination condition is met and output the result if it is met; otherwise, return to Step 2.

#### The algorithm flowchart of HNIGA is shown in Figure 3.

4.1. Solution Encoding. In the fault detection coverage problem in IWSN, one of the most important things is to encode the coverage relationship matrix C and monitoring relationship matrix S. In the coverage relationship matrix C, if the target t is within the coverage radius of the sensor s, then  $c_{t,s} = 1$ . The number of 1 in the coverage relationship matrix C is the code length of the population. The dimension D of the individuals in the population is the total number of targets successfully sensed by all sensors.

$$D = \sum_{t=1}^{T} \sum_{s=1}^{S} c_{t,s}.$$
 (9)

The coverage relationship matrix between the node and the monitored object is as shown in equation (10). The underlined values in matrix C are randomly coded.

$$C = \begin{bmatrix} 0 & \underline{1} & \underline{1} & 0 & \underline{1} \\ \underline{1} & 0 & \underline{1} & \underline{1} & \underline{1} \\ \underline{1} & \underline{1} & \underline{1} & 0 & 0 \\ \underline{1} & 0 & \underline{1} & 0 & \underline{1} \\ 0 & \underline{1} & 0 & 0 & \underline{1} \end{bmatrix}.$$
 (10)

The monitoring relationship matrix S is shown in equation (11). When the value of the underline in matrix C is 1, the value of the corresponding position in R is recoded, and the position of the value 0 remains unchanged. In the recoded matrix, 1 and 0, respectively, indicate whether the target is successfully monitored or not.

$$S = \begin{bmatrix} 0 & \underline{1} & \underline{0} & 0 & \underline{1} \\ \underline{0} & 0 & \underline{1} & \underline{1} & \underline{1} \\ \underline{0} & \underline{0} & \underline{1} & 0 & 0 \\ \underline{1} & 0 & \underline{1} & 0 & \underline{0} \\ 0 & \underline{1} & 0 & 0 & \underline{1} \end{bmatrix}.$$
 (11)

4.2. Initialization of Antibody Population. In the fault detection coverage problem in IWSN, small changes in the initial conditions will lead to entirely different subsequent state changes in a chaotic phenomenon, which is called the randomness and ergodicity of the chaotic phenomenon. Due to these characteristics, combining chaotic methods and evolutionary algorithms will produce some more excellent performance, such as increasing population diversity and jumping out of locally optimal solutions.

In the initial antibody group, adding the chaos operator can improve the algorithm's global search ability and avoid premature convergence. The one-dimensional Logistic mapping is as follows.

$$b_{g+1} = \mu \times b_g \times \left(1 - b_g\right), \tag{12}$$

$$A = \begin{cases} 0 & b_g \le 0.5, \\ 1 & b_g > 0.5. \end{cases}$$
(13)

In formulas (12) and (13),  $b_g$  is a random number between 0 and 1, and g is the number of iterations. The generated chaotic sequence consists of random decimals between 0 and 1.  $\mu$  is the control parameter. When  $\mu \in (3.5699, 4]$ , the system is in a chaotic state; when  $\mu = 4$ , the system reaches a completely chaotic state.

4.3. Affinity Evaluation. In the optimization problem of the fault detection coverage problem in IWSN, increasing the number of targets monitored by the sensor is the main goal to be optimized by the HNIGA. Its affinity can be calculated by formula (4).

4.4. Selection. The function of the selection operator is to select antibodies from the antibody population to form a new antibody population. The basis of selection is the calculation of the objective function of the individual, and its main purpose is to avoid the loss of valuable information in the HNIGA. Antibodies with higher affinity are more likely to be selected. However, the selection operation is not solely based on the affinity from high to low. However, according to the affinity, each antibody's probability in the population being inherited to the next generation population is calculated through the roulette wheel selection strategy. Antibodies with higher affinity also have the possibility of being eliminated, and antibodies with low fitness also have the possibility to pass on to the next generation.

The roulette selection strategy is used to calculate the probability of each antibody in the population inheriting the next generation population based on the affinity. The probability of each antibody being inherited to the next gen-

TABLE 1: Parameter settings of HNIGA.

	Evolutionary algebra	Antibody population	Number of memory antibody sets	Mutation probability	
HNIGA	100	40	10	0.08	

eration is the proportion of its affinity in the total affinity of the entire population. Therefore, the antibody selection is made through the roulette strategy. The higher the antibody affinity, the greater the probability that the antibody will be selected. The probability of entering the next generation can be calculated by formula (14).

$$P = n \times \frac{f(x)}{\sum_{i=1}^{n} f(x_i)},$$
(14)

where P is the expected value of being selected, n is the population number, x is the number of the individual in the population, and f(x) is the affinity of the antibody. By selection operator, it is possible to make the offspring individuals keep approaching the optimal solution in the optimization process of the genetic algorithm until the optimization is completed.

4.5. Crossover. The role of the crossover operator is to generate new antibodies. The crossover operator makes the homologous chromosomes form new chromosomes after mating, which determines the global search ability of HNIGA. Thus, it makes the crossover operator an essential part of HNIGA. The offspring produced by the crossover operator can inherit the essential characteristics of the parent. The crossover operator is mainly divided into two steps. The first is to determine the position of the crossover point in the crossover process according to the calculation of the crossover probability, and the second is to determine the way of swapping genes according to the design of the crossover operator. As shown in Figure 4, at present, standard crossover methods include single-point crossover, double-point crossover, and multipoint crossover. The difference between them lies in the number of crossover points randomly set in the individual coding, and then, these points exchange part of the chromosomes of two paired individuals. The schematic diagram of the crossover operation is as follows.

4.6. Immune Mutation. After cross-recombination is antibody variation, the individual variables of the offspring mutate with a small probability or step length. The probability or step length of the variable transformation is inversely proportional to the dimension and has nothing to do with the population size. According to research, mutation itself is a kind of local random search, combined with selection and recombination operators, to ensure the effectiveness of HNIGA, at the same time, the diversity of the population is guaranteed to prevent premature convergence.

4.7. Niche Crowding Operation. Combine the memory antibody group containing *D* individuals with the new population



FIGURE 5: The coverage of successfully monitored targets varies with algorithm iteration under conditions of Table 2: (a) 50 m sensing radius, 100 sensors. (b) 60 m sensing radius, 100 sensors. (c) 70 m sensing radius, 100 sensors. (d) 80 m sensing radius, 100 sensors.

TABLE 2: The simulation conditions in Figure 5.

	Sensing range	Number of targets	Number of sensors
Figure 5(a)	50	100	100
Figure 5(b)	60	100	100
Figure 5(c)	70	100	100
Figure 5(d)	80	100	100

containing *N* antibodies acquired by immune operation evolution to generate a new population, which contains D + N antibodies. Then, calculate the Hamming distance between antibodies  $X_i$  and  $X_i$  in this new population.

$$d_{i,j} = \operatorname{dist}(X_i, X_j) = \operatorname{sum}(X_i \oplus X_j), \tag{15}$$

where  $i \in (1, 2, 3\dots, M + N - 1)$ ,  $j \in (i + 1, i + 2, \dots, M + N)$ , and the function sum() is used to calculate the number of bits







FIGURE 6: Covered target number: (a) sensing radius of 55 meters; (b) sensing radius of 65 meters; (c) sensing radius of 75 meters; (d) sensing radius of 85 meters.

with the value of 1 in the *XOR* result. When  $d_{i,j}$  is less than the average distance *l*, compare the fitness of the antibodies  $X_i$  and  $X_j$ ; then, a penalty function is given to antibodies with higher affinity.

4.8. Find the Optimal Solution. In the fault detection coverage problem in IWSN, the purpose of this paper is to maximize the fault detection coverage. Continuous iterative evolution of the population usually produces antibodies with higher affinity. The iterative optimization process of HNIGA is repeated until the iteration reaches the termination condition and the algorithm ends. Finally, the algorithm will output the antibody with the highest affinity value as the best way to solve the problem.

TABLE 3: Number of sensor deaths during each round of monitoring.

Round	1	2	3	4	5	6	7	8	9	10
Dead	1	2	2	2	1	1	1	1	3	5
Round	11	12	13	14	15	16	17	18	19	20
Dead	1	1	1	2	1	2	2	3	2	2
Round	21	22	23	24	25	26	27	28	29	30
Dead	3	2	5	1	4	1	5	4	2	3
Round	31	32	33	34	35	36	37	38	39	40
Dead	3	1	2	3	2	1	3	5	1	1
Round	41	42	43	44	45	46	47	48	49	50
Dead	2	1	1	1	2	1	1	1	1	1



FIGURE 7: Target coverage under different periods.

## 5. Simulation

In this section, which is aimed at the problem of fault detection coverage and network lifetime in IWSN, this paper compares the optimization effect of HNIGA with traditional SA and GA through simulation. The hardware platform used in this experiment is a Ryzen5 3500x computer with 16 GB memory, and the software platform is MATLAB. In this case, the objective function (4) is used to calculate the number of targets successfully detected in the IWSN.

In the simulation, the sensing area is set to  $400 \times 400m^2$ , and 100 targets and 100 industry wireless sensor nodes are randomly distributed in this area. Assuming that each industry wireless sensor can monitor up to 4 targets, each target point must be monitored by 3 industry sensor nodes in the same period.

In HNIGA, the number of antibodies is 40, and the number of iterations is 100. Table 1 shows the detailed parameters of HNIGA, and the simulation results of the algorithm are shown in Figures 5(a)-5(d).

Figures 5(a)-5(d) are comparison diagrams of target coverage of HNIGA, SA, and GA when the industry sensor's sensing range is 50 m, 60 m, 70 m, and 80 m, respectively, and Table 2 shows the simulation conditions in Figure 5.

In (a), the monitoring radius of sensors is set to 50 m, and the number of sensors and target points are both 100. After optimization by HNIGA, the fault detection coverage can reach 83.8%, and the fault detection coverage optimized by SA can reach 80.6%, while fault detection coverage optimized by GA can reach 76.7%. In (b) except that the monitoring radius of the sensor is set to 60 meters, the other parameter variables do not change, and the maximum coverage of targets that can be monitored through the fault detection schemes optimized by HNIGA, SA, and GA are 92.9%, 87%, and 86.5%, respectively. In (c), monitoring radius of the sensor is set to 70 meters, and the maximum coverage of targets that can be monitored by the fault detection scheme optimized by the three algorithms are 95.6%, 93.8%, and 89.8%, respectively. In (d), monitoring radius of the sensor is set to 80 meters, and the fault detection coverage optimized by HNIGA, SA, and GA can reach 96.2%, 94.0%, and 90.2%, respectively.

As shown in Figure 6, it can be seen that with the increasing number of sensors in the network, the number of successfully monitored targets is also increasing. By comparison, it is obvious that HNIGA always has better optimization performance than the other two algorithms under different monitoring capabilities.

In IWSN, the network nodes are supplied with energy from the batteries they carry, which have a limited charge, and as time passes, the nodes' energy is continuously depleted. Since the energy of sensor nodes is normally distributed, it is unlikely that all nodes will stop working simultaneously due to energy depletion. However, all sensor nodes will stop working one after another. In this process, the monitoring sensors in the whole monitoring network will be reduced continuously, and the coverage will be reduced accordingly.

To verify the optimization effect of HNIGA on the network lifetime, we assume that 100 sensors with a radius of 50 m can carry out 50 rounds of monitoring at most, and a certain number of sensors will run out of energy and stop working in each round. At the beginning of each round of monitoring, we use HNIGA, SA, and GA to optimize the network and calculate the network coverage. The number of sensors dead in each round is shown in Table 3. The target



FIGURE 8: The maximum number of monitoring rounds of the three algorithms.

coverage under different periods is shown in Figure 7. The number of monitoring groups for different algorithms is shown in Figure 8.

From Figure 7, we can see that without considering that the network will stop working when the monitoring coverage is less than 50%, the IWSN optimized by HNIGA is always better than the other two algorithms in terms of target coverage. Considering the QoS of IWSN, the whole network will stop working when the target coverage rate is lower than 50%. From Figure 8, we can see that the IWSN optimized by HNIGA can complete 22 rounds of monitoring. However, the IWSN optimized by SA and GA can only complete 19 rounds and 17 rounds of monitoring, respectively. Since the coverage of the network optimized by the HNIGA is always higher than the other two algorithms, the IWSN optimized by HNIGA will be able to maintain a longer lifetime.

#### 6. Conclusions

This paper proposes a novel hybrid niche immune genetic algorithm to optimize the fault detection coverage problem in IWSN. This algorithm has advantages in maximizing the number of monitored target points. Both HNIGA and traditional GA are based on population evolution. However, the difference is that HNIGA introduces chaos operator to overcome the problem that GA is easily affected by the initial population, and niche technology is introduced to increase the diversity of individuals at the same time. Besides, compared with SA, HNIGA is based on biological evolution as a prototype and has better convergence. When the calculation accuracy is required, the calculation time of HNIGA is less, and the robustness is high. Therefore, the proposed HNIGA has distinct advantages for fault detection in IWSN. To verify the algorithm's optimal performance, this paper designed a mathematical model of the target monitoring problem, and a large number of simulations are performed. Simulation

results show that in the case of different perception radius, compared with SA and GA, HNIGA has a better optimization effect, avoids falling into the local optimum, effectively increases the fault detection coverage, and extends the lifetime of the whole network.

## **Data Availability**

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

#### Disclosure

The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript or in the decision to publish the results.

#### **Conflicts of Interest**

The authors declare no conflict of interest.

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