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Design of an Intelligent Monitoring System for the Risk of Powerhouse Flooding in Hydropower Stations Based on Lora Sensors

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SUMMARY: *This paper builds an intelligent supervisory system for flooded plants in hydroelectric power plants using the LoRa technique to address the shortcomings of traditional safety supervision of flooded plants in hydroelectric power plants, such as inefficiency and lack of wireless data transmission. The upgraded particle swarm is used in conjunction with adaptive simulated annealing techniques to solve a multi-parameter objective optimum transmission model that aims to increase LoRa transmission performance. The study's findings demonstrate that the best multi-parameter transmission strategy described in this work can be used to construct LoRa terminal transmission, which can both meet distance transmission requirements and lower power consumption during data transfer. The intelligent supervisory system's packet loss rate in the open environment test was less than 33% within 2 km, and the LoRa module's power consumption dropped by 33.33% to 94.75% when compared to the NDD86A. This demonstrates LoRa transmission's supremacy. Both low-power transmission and accurate monitoring data collection are possible.*

KEYWORDS: *Lora sensor; intelligent monitoring system; parameter optimization; SA; PSO; hydropower station*

1 Introduction

In recent years, hydroelectric power plant flooding plant accidents have occurred frequently at home and abroad, and the main causes of the accidents include heavy rainfall, mudslides, failure of electromechanical equipment, and improper operation [1]. In 2009, the top cover fastening bolts of the turbine at the Sayan-Shushensk hydropower plant in Russia broke, throwing out the top cover and runner and causing flooding of the plant. In July 2013, a mudslide triggered by heavy rainfall at Sichuan's Wulangtian Hydropower Station caused the riverbed level to rise, and floodwaters crossed the floodwall, inundating the generator floor and below of the plant. In September 2016, Henan Huilong Pumped Storage Power Station flooded its plant due to a leaky turbine roof. In 2021, flooding plant was caused by the failure of diversion steel pipe boring in Guanzhou hydropower station in Sichuan. Flooded plant accidents are usually sudden, complex and urgent, which may bring significant economic losses and seriously threaten the operation safety of hydropower plants and the life safety of personnel [2-5].

Existing research has primarily focused on identifying flooded-plant risk factors, looking into hidden dangers and risk-control measures, developing monitoring and warning systems, and creating emergency-response plans in order to strengthen flood-risk prevention in power plants. This has improved the overall prevention capability of flooded plants. In addition to

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introducing a state-based static Probabilistic Risk Assessment (PRA) framework that can be used for power plant inundation monitoring, Ma, Z et al. proposed a Simulation-Based Dynamic Flood Analysis (SBD-FA) approach that specifically covers flood hazard analysis, flood vulnerability assessment, facility response modeling, safety warning analysis, and probabilistic risk evaluation [9]. Internal water intrusion is a major safety risk for power plants, according to Qavi, A. et al. Based on this, they investigated the safety impact of a probabilistic safety assessment (PSA) technique for internal water infiltration in such plants using a case study [10]. Berg, H. and Krauss, M. examined the impact of major flood occurrences on nuclear power plants and assessed plant safety hazards using a hierarchical probabilistic assessment approach that included both probabilistic and deterministic elements for external flooding [11]. Kim, B. et al. performed a two-dimensional assessment of flood risk at a power plant using the tidal water level as a boundary condition, computed surface roughness coefficients based on land-use features like buildings, roads, and curbs, and used Localized Intense Precipitation (LIP) analysis to estimate flood risk caused by extreme rainfall [12].

With the rapid development of artificial intelligence, big data, Internet of Things, sensors and other electronic information technologies, it has become possible to use AI technology to realize intelligent inspection of power plants [13]. Power plants have begun to develop towards digitalization and intelligence, through the use of surveillance cameras, sensors and other equipment can transmit the real-time picture of the power plant, the data acquired by the sensors to the background for pre-processing and analysis and feedback, capturing the operational status of the equipment in a timely manner, and realizing the all-round supervision of the power plant by the operation and maintenance personnel [14-17]. Wang, Y et al. designed an intelligent inspection system program for hydropower plants based on digital twin technology, which integrates real-time data acquisition, online monitoring, video surveillance and predictive alarms to provide strong technical support for intelligent operation and maintenance in hydropower industry [18]. Fang, W et al. proposed a fault diagnosis and condition monitoring method applied to hydroelectric power plants by using an intelligent detection technique based on convolutional neural network (CNN), which was shown to perform well in recognizing abnormalities and issuing early warnings, and to be able to issue warnings and provide feedbacks in a timely manner in response to abnormalities, such as water flooding [19]. Manikandababu, C et al. designed a novel remotely operated vehicle (ROV) equipped with a high resolution camera, advanced sensor technology, and a microprocessor that combines CNN and VGG16 architectures to realize intelligent monitoring of hydropower facilities [20].

Sensors are an important cornerstone for the realization of testing and automatic control, but also a key means of obtaining various types of environmental information, through the large-scale deployment of sensor equipment, can monitor and collect a variety of environmental information in real time, thus providing strong technical support for the hydroelectric power plant to reduce the manual maintenance and operation and enhance the production and economic efficiency [21, 22]. Qin, Y et al. pointed out that smart sensor networks in hydroelectric power plants play an important role in enhancing the intelligence of hydroelectric power plants, reducing the cost of safe operation and maintenance of hydroelectric power plants, and improving the computational and analytical capabilities of hydroelectric power plants [23]. Magrini, L et al. constructed a structured hydroelectric power plant safety monitoring system which utilizes XML format for data transmission and XMPP protocol for communication between sensors and monitoring and data acquisition system, the monitoring system is compliant with IEEE Sensei-loT standard [24]. To lessen subjectivity in the monitoring and behavioral prediction of hydroelectric power plants, Calarasu, A. et al.

created decision-support platforms using expert-system modules. By using multi-sensor information fusion techniques, these systems can foresee hazardous circumstances like floods, diagnose structural problems or abnormalities, and monitor plant detection data [25]. A novel structural monitoring system for hydropower plants based on a distributed smart-sensor architecture was also suggested by Strojan, N. et al. This system, which takes the shape of a hierarchical network, sets up plant sensors, collects and displays sensor data, and presents a software program for system administration [26].

LoRa (Long Range) is a long-distance, low-power wireless transmission technology derived from linear spread-spectrum modulation and introduced by SemTech, USA, in 2013 [27]. Incorporating LoRa technology into the design of intelligent monitoring systems for hydropower-station flooded-plant risk can solve the problem of same-frequency interference in wireless communication. In other words, when terminal signals with different frequencies are received simultaneously, the system can process them by separating frequencies, which allows parallel data reception from the sending side and improves overall system throughput [28–30]. In addition, LoRa employs Forward Error Correction Coding (FEC) to improve the reliability of information transmission [31]. Nevertheless, owing to technical constraints, intelligent monitoring systems for hydropower plants have not yet formed a fully mature LoRa deployment scale, and several unresolved issues remain in practical application. Continued research based on real operational needs is therefore still necessary.

This article uses LoRa technology to develop an intelligent risk-monitoring system for flooded hydropower facilities. The system, which consists of endpoint acquisition equipment, relay transmission units, a cloud platform, a server, and other functional modules, is implemented utilizing the ThingsBoard platform, LoRa communication, and embedded technology through the integrated management of hydropower safety data. The matching parameters of LoRa are improved in order to enhance LoRa transmission performance from the intelligent monitoring system's application standpoint. Three important LoRa characteristics are used to build an objective function with the optimization goals of minimal energy consumption, maximum transmission distance, and high robustness of LoRa wireless communication. An enhanced particle swarm methodology in conjunction with adaptive simulated annealing yields the best solution after the initial multi-objective optimization work is converted into a single-objective issue using a normalization technique and a weighted-sum approach. The behavior of the model under various transmission lengths is then investigated, and the optimal and non-optimized scenarios are compared in terms of energy consumption, transmission distance, and data-transmission resilience. Lastly, the system's performance is assessed and its power consumption and packet loss rate are examined.

2 Overall system design

2.1 Overall structure

Technological progress has made the construction of intelligent hydropower plants more and more mature, in addition to the traditional wired network access, stable, high-speed and secure plant-wide wireless network coverage is one of the important infrastructures in the intelligent operation and maintenance work of hydropower plants. This study describes the creation of an intelligent monitoring system for risk management of flooded power plants of hydropower stations using Lora communication technology. There are two types of wireless communication technology utilized in industry: wide-range network wireless communication technology and short-range wireless communication technology. Low cost, low power consumption, and extended transmission distance are prerequisites for system design. After weighing the advantages and disadvantages of several wireless communication technologies, this article concludes that LoRa technology is better suited for creating this system. Long-distance transmission using LoRa wireless spread spectrum communication technology can be accomplished at the expense of data rate; typically, the data rate is less than 50 kbps, and the transmission distance in an open region is up to 10 km.

The overall architecture of the Lora sensor-based intelligent monitoring system for hydropower plant flooding risk is shown in Fig. 1, which consists of endpoint collection equipment, relay data transmission unit and cloud platform.

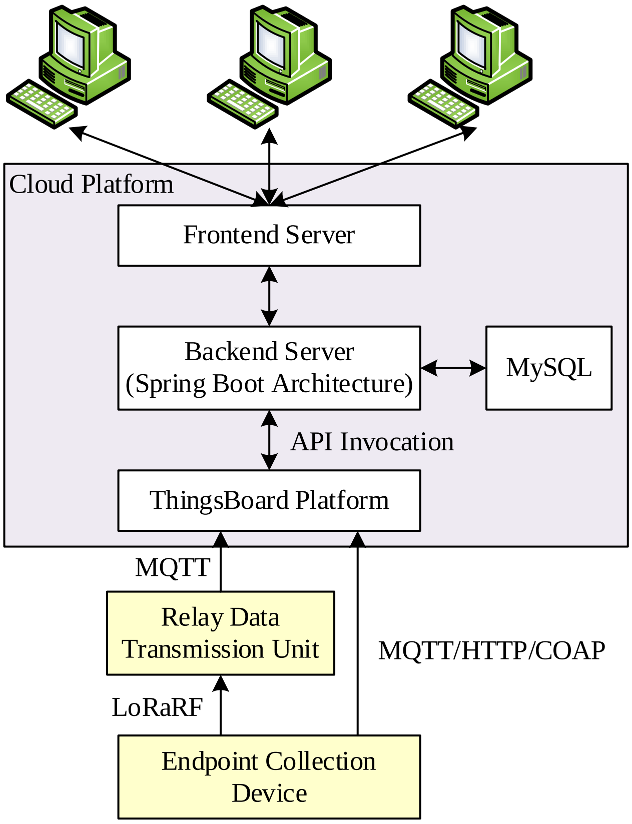


Figure 1: The overall architecture of the intelligent monitoring system

2.2 Module Composition

2.2.1 Endpoint acquisition equipment

The endpoint acquisition equipment realizes the accurate real-time acquisition of indicators such as environmental parameters (e.g., temperature, flow, water level, etc.) and equipment monitoring data (e.g., generator vibration, pressure and temperature, etc.). For endpoint acquisition devices that cannot be directly connected to the cloud platform, LoRa communication is used in combination with relay data transmission units. For endpoint acquisition devices that can directly access the cloud platform, data uploading to the cloud is realized through MQTT, HTTP and COAP communication methods.

2.2.2 Relay data transmission unit

The relay data transmission unit collects data information from all endpoint collection devices in the region through downlink LoRa routing nodes and stores the data locally before uploading it to the cloud platform through MQTT communication to realize remote networking transmission and data entry operation of on-site hydropower devices.

2.2.3 Cloud platforms

The cloud platform is the data storage and remote monitoring interactive interface of the entire hydropower station flooded plant risk intelligent monitoring system. By building the ThingsBoard platform to receive the data sent by the endpoint collection devices, it realizes the access to the devices and products.ThingsBoard supports connecting multiple devices downward, and provides multiple open API interfaces upward, so that the user can realize the control of the devices by sending commands.

2.2.4 Back-end servers

The back-end server utilizes the API provided by the ThingsBoard platform to realize the data interaction between the host computer application software and the ThingsBoard platform, and obtains the data uploaded by the remote endpoint collection device at regular intervals. SpringBoot technology is used for the architecture to store the received data in MySQL and provide the API interface for the front-end according to certain specifications.

2.2.5 Front-end servers

The front-end server uses the API provided by the back-end to get the data, so as to realize the functions such as rendering the page and displaying the data. The front-end development uses Vue technology, which contains several sets of technology stacks, such as vue-cli, vue-router, webpack, ElementUI, etc. It mainly sends requests such as get, post, etc. to the back-end through Axios to get the data from the back-end, and then displays it visually.

3 SA-IPSO-based multi-parameter objective optimization for LoRa

In this chapter, the multi-parameter optimization model of LoRa is designed, and an optimized particle swarm optimization algorithm using adaptive simulated annealing is used to perform optimization, following the completion of the design of the hardware part of the intelligent monitoring system against the risk of flooded plants in hydropower plants. This ensures that the parameters set can meet the conditions of transmission distance of the system while having good robustness and consuming the least amount of power.

3.1 LoRa Parameter Optimization Objectives

After discussing LoRa modulation and demodulation techniques, it is discovered that bandwidth (BW), spreading factor (SF), and coding rate (CR) are the key factors influencing LoRa transmission efficiency. LoRa module communication capability will be significantly improved by improving the three fundamental design parameters of LoRa, which are SF, BW, and CR.

First, we should observe that the three most crucial characteristics of LoRa radio transmission technologies—low power consumption, long transmission distance, and high robustness—contradict each other. However, the system has to have these three characteristics in order to meet the requirement for intelligent monitoring of the flooding hazards associated with hydroelectric facilities. Finding the best balance between these three characteristics therefore becomes a difficulty, turning the issue into a multi-objective optimization problem of LoRa properties. The data transmission rate and the amount of time needed for signal propagation in the air determine how much electricity is used. The power consumption of LoRa Q may be determined by taking into account all of the aforementioned power-affecting parameters.

$$Q = f_Q\left(DR, T_{packet}\right) = f_Q\left(SF, CR, BW, n_{preamble}, PL, DE, H\right) \tag{1}$$

where: DR is the data rate, T_{packet} is the over-the-air transmission time, SF is the spreading factor, BW is the bandwidth, CR is the coding rate, $n_{preamble}$ is the length of the leading code of the packet, PL is the number of bytes of the payload, DE is whether to enable the low-data-rate optimization , H is whether header is enabled, and 1 means no header exists. The secondary impact parameters $n_{preamble}$, PL, DE, and H values of system power consumption are fixed as shown in equation (2):

$$\begin{cases} n_{preamble} = 8 \\ PL = 32 \\ DE = 0 \\ H = 1 \end{cases} \tag{2}$$

The power-energy loss of the system can be simplified from Eq. (1) to Eq. (3) by considering only three key influencing factors, namely, spreading factor, modulation bandwidth and coding rate:

$$Q = f_Q\left(DR, T_{packet}\right) = f_Q\left(SF, CR, BW\right) \tag{3}$$

Transmission rate and reception sensitivity are the key factors that determine the transmission distance of the system, and the other secondary factors are set as fixed values. The transmission distance of LoRa D is expressed as shown in equation (4):

$$D = f_D\left(L\right) = f_D\left(SF, CR, BW\right) \tag{4}$$

Robustness is considered only for SF, CR and BW, and the robustness R of the system can be expressed as equation (5):

$$R = f_R\left(SF, CR, BW\right) \tag{5}$$

Therefore, a multi-objective optimization method based on LoRa parameters is proposed to optimize multiple objectives at the same time to achieve the optimal performance of the system and to achieve the requirements of the longest transmission distance, the lowest power consumption for transmission and the best robustness, viz:

$$\begin{cases} \min Q = \min\ f_Q(SF, CR, BW) \\ \max D = \max\ f_D(SF, CR, BW) \\ \max R = \max\ f_R(SF, CR, BW) \end{cases} \tag{6}$$

The optimization problem is transformed from a multi-objective one into a single-objective one using the weighted sum approach and normalization in order to further simplify the multiple goals problem. First, the three quantitative objective functions (Q, D, and R) that influence LoRa's performance are normalized. The objective function may then be transformed into a dimensionless objective function by dividing it by the base value, which ensures that the preprocessed data falls within a specific range before using the weighted sum method to transform it into a single objective function by multiplying the dimensionless objective function above by corresponding weights. The new objective function F is then obtained by taking the sum and maximizing the objective function in the range, as indicated in equation (7):

$$\max F = \max\left[-w_1 \frac{f_Q}{f_{Q'}} + w_2 \frac{f_D}{f_{D'}} + w_3 \frac{f_R}{f_{R'}}\right] \tag{7}$$

where: w_1, w_2, w_3 are weighting coefficients and satisfy the conditions as shown in equation (8):

$$\begin{cases} w_i \in [0,1] \\ -w_1 + w_2 + w_3 = 1 \end{cases} \tag{8}$$

The maximum value of the dimensionless function F is solved, and the found optimal solution is the set of parameters that make the LoRa transmission performance optimal, in which the key influential parameters SF, BW, and CR need to be optimized within a certain range of combinations, with the constraints as shown in Eq. (9):

$$\begin{cases} SF = \{5,6,7,8,9,10,11\} \\ BW = [7.5, 9.8, 14.7, 21.2, 30.5, 40.8, 60.4] \\ CR = [0.5, 1.5, 2.5, 3.5] \\ w_i = [0,1] \\ -w_1 + w_2 + w_3 = 1 \end{cases} \tag{9}$$

3.2 Model Solution Methods

3.2.1 Simulated Annealing Algorithm

The idea of simulated solid annealing is employed in the Simulated Annealing Algorithm (SA), wherein the solid material is heated to a high temperature, which causes the molecules to form a chaotic and disordered structure. However, as the material cools down gradually, the molecules stabilize and adopt a solidified structure, which causes the solid material to become stable as well.

(1) Metropolis Criterion

The probability that a particle tends to equilibrium at temperature T is $\exp\left(-\Delta E / (kT)\right)$, where E is the internal energy at temperature T, ΔE is the number of changes in it, and k is Boltzmann's constant. the Metropolis criterion is often denoted as:

$$P=\begin{cases}1 & if\ E(x_{new})<E(x_{old})\\ \exp\left(-\dfrac{E_{x_{new}}-E_{x_{old}}}{T}\right) & if\ E(x_{new})\geq E(x_{old})\end{cases} \quad (10)$$

The initial state X_{old} of the particle relative position is given first, and the energy of the current state as a solid is $E_{x_{old}}$. Then a small change occurs randomly with the ingestion device to get a new state X_{new}, the energy of the new state is $E_{x_{new}}$, and the acceptance probability of the system changing from state X_{old} to state X_{new} is P. So at temperature T, the current state to new state rule is as follows: if $E_{(x_{old})}\leq E_{(x_{new})}$, then X_{new} is accepted as the current state. Otherwise, with probability $\exp\left(-\dfrac{E_{x_{new}}-E_{x_{old}}}{T}\right)$ accept the state as the current state, otherwise keep X_{old} as the current state.

(2) Cooling schedule

Cooling is defined in simulated annealing algorithms as the process of cooling an algorithm so that it undergoes multiple transitions to the "current optimal solution," each with a probability near 1, and converges "slowly" to return to the approximate optimal solution..

The basic flow of the simulated annealing algorithm is as follows:

1) The initial control temperature is set to T_0, the Markov chain length is L_0, an initial solution is randomly picked as i_0 among the feasible solutions, the current optimal solution is $i=i_0$, the number of iterations $k=0$, and the cooling function $T_k=h(k)$.

2) A random perturbation occurs with the ingestion device to obtain a new solution j in the feasible solution space.

3) Use the Metropolis criterion to determine whether to accept the new solution:

(a) If $f(i)\geq f(j)$, the new solution j is accepted, when the optimal solution $i=j$.

(b) If $f(i)<f(j)$, accept the new solution j according to the probability, i.e., if $\exp\left(-\dfrac{f(i)-f(j)}{T_k}\right)>random\left[0,1\right)$, accept the new solution j, and at this time the optimal solution $i=j$, otherwise, reject j. the optimal solution is still i.

4) Repeat steps 2 and 3 for L_0 times to obtain an optimal solution under the Mahalanobis process with chain length L_0.

5) First determine whether the pre-set stopping criterion is satisfied, if so, the algorithm is terminated and the optimal solution is output, otherwise, the next step is executed.

6) The number of iterations $k=k+1$, the solution obtained in step 4 is updated to the optimal solution of the function, the Markov chain length becomes L_{k+1}, and the temperature function becomes T_{k+1}, and return to step 2.

3.2.2 Particle Swarm Optimization Algorithm

Animals search for food through cooperation, so do bird flocks, their members share their flight experience and location information through information exchange, under the leadership of this information, the individuals in the flock will search for food in the direction of food, and ultimately find the target, for the conditions of food distribution, the advantage of this cooperation is much greater than the disadvantage caused by competition. The particle swarm optimization (PSO) algorithm simulates the individuals in the flock as particles. Individual particles search and update their own position information and speed in the iteration process, and then through the exchange of information between the populations, according to the “guiding” information, then continuously update their own speed and position to search in the direction of the target, and then search the majority of the search space to find the target. Then it searches most of the search space to find the target. In the search space, the position and speed information is represented by $x_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{id})$ and $v_i = (v_{i1}, v_{i2}, v_{i3}, ..., v_{id})$ to express it. Then the x_i and v_i of the particles are updated as:

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 [p_{best} - x_{ij}(t)] + c_2 r_2 [G_{best} - x_{ij}(t)] \quad (11)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (12)$$

where t is the number of iterations, c_1 and c_2 are constants that play a role in acceleration, in general $c_1 + c_2 \leq 4$. r_1 and r_2 are two random numbers, $p_{best} = (p_{i1}, p_{i2}, ..., p_{iD})$ is the individual position and $G_{best} = (g_1, g_2, ..., g_D)$ is the global optimal position. For the velocity $v_{ij}(t)$ the size can be controlled by artificially setting its upper limit $V_{\max}$ and lower limit $V_{\min}$. If the value of $v_{ij}(t)$ is large it can enhance the convergence speed. However, because of the large value of $v_{ij}(t)$, it is easy to miss the optimal solution, which leads to a decrease in the accuracy of the algorithm. If the value of $v_i(t)$ is small, it is beneficial to improve the local search ability and thus enhance the convergence accuracy of the algorithm, but it is easy to fall into the local optimum, unable to jump out of it, which ultimately leads to the possibility of not being able to search for the real target. The algorithm process is as follows:

(1) Initialize the parameters.

(2) Evaluate the fitness value F_{it}.

(3) If $F_{it} > P_{best}$, replace P_{best} with F_{it}.

(4) If $F_{it} > G_{best}$, replace G_{best} with F_{it}.

(5) Update the particles $v_i(t+1)$ and $x_i(t+1)$.

(6) If $t \geq T$ exit.

(7) Otherwise return to (2).

3.2.3 A-IPSO Algorithm

In addition to significantly improving global optimization performance, the design introduces a novel optimization scheme that is a variation of the classical particle swarm optimization approach. This allows for its integration with the simulated annealing approach to create a hybrid scheme of an adaptive particle swarm optimization approach (SA-IPSO). Utilizing the advantages of both strategies while resolving their respective shortcomings is what constitutes innovation.

The algorithm is realized as follows:

(1) Initialize the initial parameters. Initial parameters are initialized by setting the initial temperature to T_star, the termination temperature to T_end, and the current temperature to T_cur, and making $T\_cur = T\_star$.

(2) Initialize the population. Randomly generate the initial population and the number of particles, initialize the individual extreme value $pbest$ as well as the group extreme value $gbest$ for each particle. Set the self-cognitive learning factors $ac1$ and $ac2$, which determine the relative influence of the particle's self-cognition and social experience on its trajectory.

(3) Compute the fitness of each particle based on the equation above to obtain the present optimum value of Pa.

(4) Ascertain if the current particle's fitness surpasses the individual extreme value; if yes, the particle's performance will be measured by updating the individual extreme value and changing the particle's position.

(5) Compare each particle's fitness to the global extreme value; if the particle's fitness is higher than the global extreme value, the subscript and particle fitness will be modified.

(6) During the pre-iteration phase, the learning factor update speed is determined using the standard learning factor update rule. Because of the simulated annealing idea, each particle's current adaptation function value will be compared to its prior value at the late iteration stage. The value of the current particle will take the place of the individual ideal value if the current adaption value proves to be superior than the prior one, the judgment is carried out, and if $exp(-\Delta P / T) > s$ (s is a random number between 0-1), then the current solution should be taken as the optimal solution of the algorithm, and the cognitive function $c1$ and inertia weight W should be adjusted to achieve the best modeling effect.

The adjustment formula of self-cognitive function is shown in equation (13), and the adjustment formula of inertia weight is shown in equation (14):

$$c1 = ac1 \times \exp\left(-t\_cur / t\_star\right) \times rannum1 \tag{13}$$

$$W = W\max + \left(W\max - W\min\right) \times (i-1)/(iwe-1) \tag{14}$$

where: $c1$ denotes the self-cognitive function, $ac1$ is the initial value of the self-cognitive function, $rannum1$ denotes the random number within 0-1, W is the inertia weight, $W\max$ is the maximum value in the weight, $W\min$ is the minimum value in the weight, and iwe is the number of inertia weight adjustment steps.

(7) Update the particle's location and velocity data based on the results of the iterative selection process.

(8) Use the basic stages of the simulated annealing algorithm to carry out the annealing process.

(9) Determine if the algorithm's stopping requirements are met, i.e., whether the method's predefined maximum iterations have been reached; if so, the process terminates and displays the optimal answer. Return to step (3) if not.

3.3 Model Test Analysis

This section utilizes Matlab to simulate the objective function in line with the algorithm flow covered in the preceding section in order to demonstrate the validity of the multi-objective optimum algorithm of LoRa based on SA-IPSO. The initial temperature and cooling rate are 800 and 0.95, respectively, the population size and particle dimension are 35 and 10, the iteration is set at 4000, and the inertia weight is 0.75.

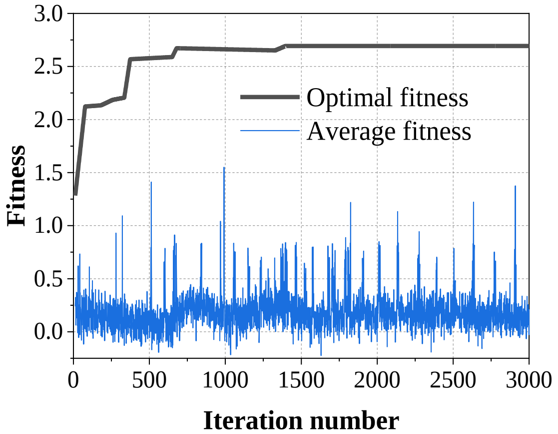
Figure 2 illustrates how the goal function varies across several runs while varying the weight coefficient of each objective function, taking into account the overall impact of energy usage, transmission distance, and data transfer resilience. Among them, Figure 2a displays the objective function change diagram with the transmission distance benchmark value of 3000 meters, while Figure 2b displays the objective function change diagram with the transmission distance benchmark value of 5000 meters. Figure 2c displays the objective function change graph with the transmission distance benchmark value of 7000 meters, whereas Figure 2d displays the objective function change graph with the transmission distance benchmark value of 10,000 meters. It is evident that the method used in this work achieves convergence results close to 700 generations.

The optimized contrasting values of parameters for each scheme are shown in Table 1. When the transmission distance is 5000 m, the optimized system energy consumption and robustness are 4.15 J and 0.94, respectively, while the unoptimized results are 5.98 J and 0.82. When the transmission distance is 10000 m, the optimized system energy consumption and robustness are 12.95 J and 0.74, respectively, while the unoptimized results are 18.03 J and 0.68. After the SA-IPSO algorithm's optimization, the system energy consumption is lower while the parameter robustness is higher for the same transmission distance. The feasibility of the multi-objective optimization method used in this paper can be seen, and the energy consumption, the farthest transmission distance, and the robustness of transmission of the data transmission of the four schemes are balanced accordingly with the existence of mutual constraints among the three objective functions. In the optimization results, 3000m, 5000m, 7000m, and 10000m are taken as the benchmark values of the optimization objectives, and the corresponding parameter values are obtained to achieve the balance of energy consumption with transmission distance and robustness. The unoptimized results clearly show the contradictory nature of the system energy consumption and transmission distance.

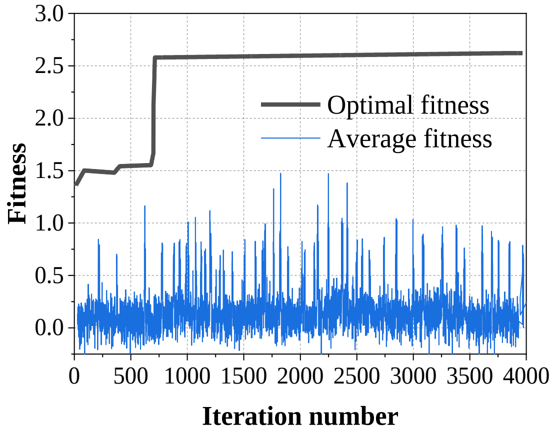
By increasing the data transfer rate according to the data transmission distance, the energy cost of the intelligent monitoring system for hydropower station flooding plant risk could be suitably decreased. Furthermore, the system's resilience would be sacrificed in order to lower its energy cost.

Table 1: Comparison of optimization results

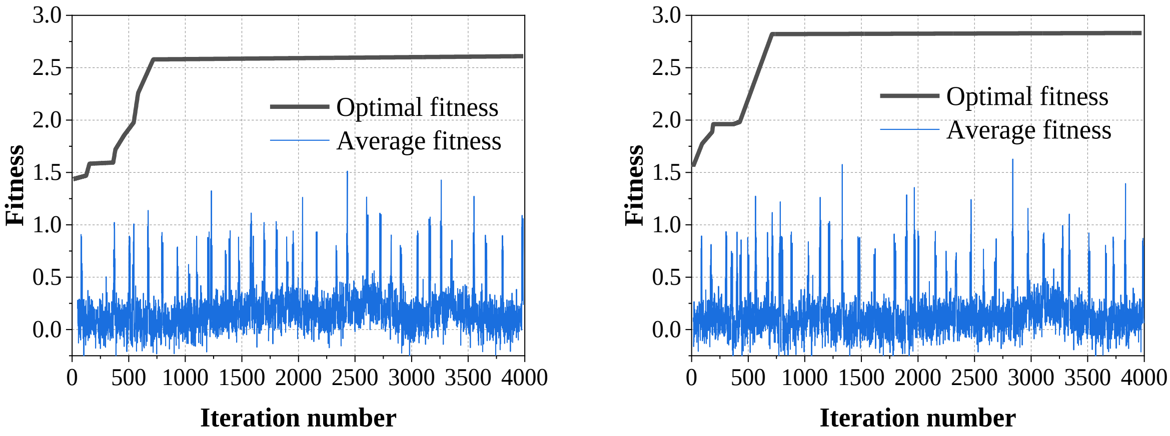
	No.	*SF*	*BW*	*CR*	System energy consumption/J	Transmission distance/m	Robustness(0~1)
Optimized result	1	7	31.53	5	1.36	3000	0.92
	2	8	10.59	4	4.15	5000	0.94
	3	10	8.79	3	8.46	7000	0.83
	4	12	7.12	3	12.95	10000	0.74
Unoptimized result	5	5	450.73	2	5.98	5000	0.82
	6	11	8.13	4	18.03	10000	0.68



(a) The distance datum is 3000m



(b) The distance datum is 5000m



(c) The distance datum is 7000m (d) The distance datum is 10000m

Figure 2: The fitness curve of the target function

4 System test analysis

This paper builds and deploys a system for testing in a hydropower station flooded plant. Each module node of the system needs a stable and reliable software and hardware design platform, and YAC9900 terminal is selected as the carrier to realize practical application. The integration of LoRa wireless communication RF module through YAC9900 terminal can simplify the design process and improve the integration efficiency. The data communication smoothness and power consumption are tested and verified.

4.1 LoRa communication distance test

The communication distance test mainly includes the LoRa communication distance test in open environment as well as in the environment with obstacles, and the test index is that the sub-node sends 250 data frames to the master node, the length of the data frame is 25 bytes, and the interval of the data sending time is 2000ms.

The packet loss rate test results of several to-be-selected LoRa parameters at different distances in an open and visible environment are shown in Fig. 3. According to the test results, it can be seen that the packet loss rate increases gradually with the increasing distance, and the packet loss rate is 0% within 0.5km~1.5km under LoRa07 integration parameters, and the packet loss rate increases from 1.64% to 26.49% at 1.5km~2.5km. At the same communication distance, the lower the LoRa parameter the higher the data transmission reliability, and therefore also easier to communicate over long distances, the packet loss rates of LoRa08, LoRa07, LoRa06, and LoRa05 are 16.81%, 5.25%, 2.15%, and 1.38% respectively for a communication distance of 2km. Then the communication distance test is conducted again for the environment with obstacles, and the test results are shown in Figure 4. It can be seen that the communication ability is greatly reduced when there are obstacles present, but it can also basically meet the demand, except for the LoRa06 integration parameter, the maximum value of the packet loss rate of the other LoRa parameters at the maximum test distance is more than 30%, and the packet loss rate of LoRa06 at 1.75km is 29.62%. In summary, the LoRa06 integration parameter is finally selected in combination with the actual application of the intelligent risk monitoring system for hydropower station flooded plant risk and based on the principle of ensuring communication quality while minimizing data transmission time.

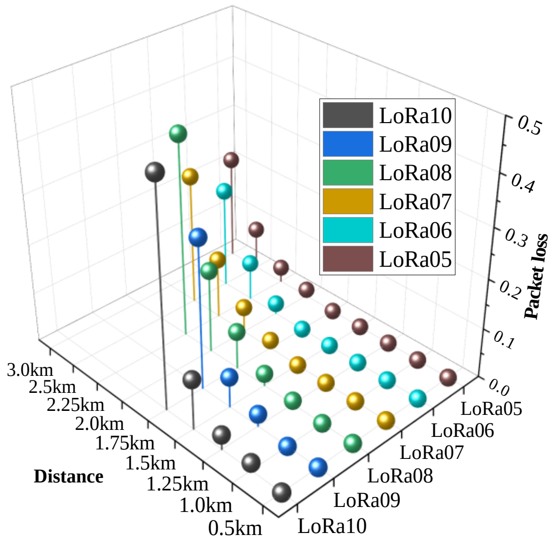


Figure 3: Communication distance test for open environment

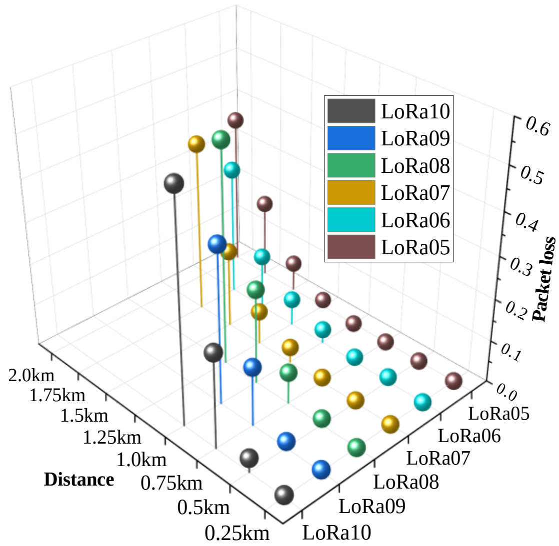


Figure 4: Communication distance test for obstructed environment

4.2 System Power Consumption Test

Testing the power consumption of LoRa modules when communicating with each other, comparing with other wireless transmission technologies, the average power consumption of each module was counted, and the results of the system power consumption test are shown in Table 2.Comparing the power consumption of LoRa modules with traditional VHF radios with ND886A (10W transmission), NB-IoT, WiFi, and GPRS, it is obviously concluded that the power consumption of LoRa module's transmit current, receive current and sleep current are significantly less than other wireless transmission methods, reflecting the advantage of reduced power consumption. Compared with ND886A, the LoRa module reduces 94.75%, 92.96%, 33.33%, and 42.86% in transmit current, receive current, sleep current, and transmit power, respectively.

Test the system's overall energy consumption while it is operating. Since the system's nodes and module equipment are configured differently, each component's energy consumption level varies. Examine how much energy LoRa modules and other hardware parts use. The overall amount of energy consumption during operation is less than 180mA. In the inactive state, less than 8mA of energy is consumed overall. The use of LoRa modules in the intelligent risk monitoring system for flood threats in hydropower plants would drastically lower the system's energy consumption.

Table 2: System power test results

Communication module	Emission current/mA	Receiving current/mA	Dormant current/mA	Transmitting power/dB
LoRa	105	10	2	20
ND886A	2000	142	3	35
NB-IoT	150	50	3	50
WiFi	130	20	6	30
GPRS	120	45	5	40

5 Conclusion

In order to maximize the efficiency of hydroelectric power plants and reduce the likelihood of accidents, risk monitoring is crucial. We employ the wireless LoRa communication technique to send the collected data to the data relay transmission module in order to create a hydropower plant flooding plant risk intelligent monitoring system utilizing Lora sensors. Then, we have embraced the front and backend separation development approach by utilizing the ThingsBoard platform for application development.

Aiming at the optimization problem of LoRa parameters, the LoRa multi-parameter objective optimization model based on SA-IPSO is constructed. The model test found that the SA-IPSO algorithm has a better convergence effect, and has strong advantages in optimization search and stability, such as in the transmission distance of 5000m, compared with the unoptimized results, the model-optimized system consumes less energy and has higher parameter robustness, which are 4.15J and 0.94, respectively, compared with the unoptimized results of 5.98J and 0.82, which satisfy the intelligent monitoring system in the traditional distance requirements while having the advantages of low power consumption and high robustness.

Although the packet loss rate in the obstructed environment is higher than the loss rate in the unobstructed environment in the intelligent monitoring system tests, it can essentially meet the communication requirements, and the packet loss smooth rate in the unobstructed environment surpasses 83% within 2km. When compared to ND886A, the transmitting current, receiving current, inactive current, and transmitting power are reduced by 33.33%–94.75%, and the LoRa module uses less energy than other comparison techniques. This suggests that reduced power consumption may be achieved by using the LoRa technique in the intelligent monitoring system. Furthermore, in order to develop the system and get a better smoothness rate and lower power consumption level during operation, additional real application practice is required. The technology is anticipated to have many uses in the future because to its certain benefits of low power consumption, long-distance communication, and high fluency rate.

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