Indian Journal of Geo Marine Sciences
Vol. 50 (11), November 2021, pp. 914-921

Fault diagnosis of the constant current remote power supply system in CUINs based on the improved water cycle algorithm

M J Zuo[a], G Xiang*[,b,c,d] & S Hu[a]

[a]College of Electronic Engineering, Naval University of Engineering, Wuhan – 430 033, PR China

[b]School of Naval Architecture and Ocean Engineering, Huazhong University of Science and Technology, Wuhan – 430 074, China

[c]Hubei Key Laboratory of Naval Architecture and Ocean Engineering Hydrodynamics (HUST), Wuhan – 430 074, China

[d]State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University, Hangzhou – 310 027, China

*[E-mail: gongxiang@hust.edu.cn]

Received 31 August 2021; revised 30 November 2021

Cabled Underwater Information Networks (CUINs) is an important platform for ocean observation where the Constant Current Remote Power Supply System (CCRPSS) guarantees the safe and normal operation of CUINs. The CCRPSS is mainly composed of the main node and underwater cables which require frequent fault diagnosis but how to improve the fault diagnosis rate is a difficult problem. This paper proposed a fault diagnosis method for the CCRPSS based on the Improved Water Cycle Algorithm (IWCA) and the multi-classifier group based on the Least Squares Support Vector Machine (LSSVM). Firstly, the multi-feature extraction method is used to obtain the characteristic information in the time and frequency domain; secondly, IWCA is established by combining the traditional Water Cycle Algorithm (WCA) with the chaotic mutation strategy, the elite memory strategy and the population reconstruction strategy. By applying 13 typical test functions to performance test, it can be found that the IWCA can effectively improve the global search ability and balance of the WCA algorithm. At last, IWCA is used to optimize the parameters of the LSSVM classifier and improve the classification efficiency. The comparisons of simulated results with traditional methods show that the proposed diagnostic model can not only obtain complete fault feature information, but also obtain the optimal classification parameters of LSSVM faster. Therefore, the proposed diagnostic method is verified to be suitable for the fault diagnosis of the constant current remote power supply system in CUINs.

[**Keywords**: Cabled Underwater Information Networks (CUINs), Constant Current Remote Power Supply System (CCRSS), Fault diagnosis, Improved Water Cycle Algorithm (IWCA), LSSVM multi-classifier group]

Introduction

Recently, with the rapid development of communication, energy, sensor and network technology, etc., as one of the most important means to explore and study the ocean, the comprehensive level of seabed observation system has been continuously improved[1]. Cable Underwater Information Networks (CUINs), as a widely used network in seabed observation system, plays an irreplaceable role in seabed biological resources mineral resources explorations, seabed hydrological monitoring and recording the impact of human activities on the ocean. Following the ground/ocean surface and space observation system, the cable underwater information network breaks the constraints of time and space in the traditional mode, and can meet the human requirements for long-term, continuous and all-weather ocean observations. CUINs consist of Shore Power Feeding Equipment (SPFE), submarine photoelectric composite cables and other related testing equipment. The power supply of CUINs comes from the shore by transmitting the power from shore to the seabed by a submarine photoelectric composite cable. Therefore, a good submarine photoelectric composite cable working well has become a prerequisite for the normal operation of CUINs. At present, remote power supply in CUINs mainly includes DC constant voltage and DC constant current[2]. The most typical submarine network with DC constant voltage remote supply system is Neptune observation network jointly established by the United States and Canada[3], and the most typical DC constant current remote power supply submarine network is DONet network built in Japan[4].

In the mooring underwater information network, the fault diagnosis and section positioning of the remote power supply system is an important guarantee for the safety and operation of the whole system. With the changes of seabed environment and geological movement having strong uncertainty, the fault diagnosis of remote supply system of cable underwater information network is becoming more and more difficult correspondingly. Thus, it is very necessary to study the simple and effective fault diagnosis method of remote supply system of cable underwater information network which can adapt to complex working environment. At present, the fault diagnosis of remote power supply system mainly uses fault diagnosis and interval positioning to determine the fault area. Meanwhile, there are many relevant research results and findings: for example, when DC power is used for power supply in DC remote power supply system in Lin *et al*.[5], the traditional AC voltage and current phase angle measurement method cannot be used for state diagnosis of trunk line. Feng[6] used the average residual value of the measured voltage to identify the open circuit fault of the constant voltage remote supply system, and locate the fault interval through the change of voltage during the open circuit. A new type of submarine information network is introduced together with the sensors, detection equipment and power supply standards which are used in the network[7]. The applications of constant current voltage source and current source technology in the remote power supply of submarine information network are systematically studied and discussed[8-12].

In fact, most of the fault diagnosis methods in the above literatures are simple and time-consuming because the limits caused by the physical characteristics of analog circuits. When the remote power supply system is in a complex and changeable working environment, the above-mentioned methods may have a diagnostic blind area. Therefore, it is urgent to study the fault diagnosis method of remote power supply system with higher efficiency and stronger applicability. In recent years, data-driven fault diagnosis methods such as Support Vector Machine (SVM)[13] and Least Squares Support Vector Machine (LSSVM)[14] have become a promising and effective approach to solve fault diagnosis. LSSVM algorithm trains the input and output of sampling data to obtain the functional relationship. Then the optimization method is adopted to search the optimal parameters to ensure that the obtained functional relationship has the minimum fitness error. At the same time, LSSVM has been used for fault diagnosis of complex systems and already achieved good results[15-18].

In present paper, aimed at better solving the problem of fault diagnosis of constant current remote power supply system, a new fault diagnosis method based on Improved Water Cycle Algorithm (IWCA) and LSSVM multi classifier group is proposed for fault diagnosis of constant current remote power supply system in CUINs. The comparisons of simulated results with traditional methods show the better capability of proposed new fault diagnosis method.

Characteristics extraction

In this paper, the fault diagnosis signal in the constant current remote supply system is a direct current, thus, the Empirical Mode Decomposition (EMD) method is used to extract the signal frequency domain characteristics for preliminary analysis. By adding a different white noise *n(t)* each time to change the extreme point characteristics of the low-frequency components in the original signal *x(t)*. As a result, the Intrinsic Mode Function (IMF) obtained by the EMD decomposition can be overall averaged. The mode confusion caused by the discontinuity of IMF in the EMD method can be cancelled by the added noise *n(t)* effectively. At last, in order to use the data information to identify the characteristics of the signal in frequency domain more clearly, the wavelet packet transform function is used to perform three-layer wavelet decomposition on the extracted IMF time series to obtain the target dimension feature vector, which is input to the classifier as a fault diagnosis basis.

Water Cycle Algorithm (WCA)

Traditional water cycle algorithm

The water cycle algorithm is an optimization algorithm proposed by Eskandar *et al*.[19], which achieves the purpose of finding the optimal solution by simulating the earth's water cycle process. With good global search capabilities, the algorithm can solve complicated system optimization problems. The population updating approach and calculation method for each iteration in the WCA algorithm are expressed by Eqs. 1 – 7. The main parameters are defined below.

$$N_{sr} = N_{river} + 1 = N_{pop} - N_{stream} \quad \ldots (1)$$

$$N_{sri} = round\left(\left|\frac{C_i}{\sum_{j=1}^{N_{sr}} C_j}\right| N_{stream}\right), i = 1,2,\cdots,N_{sr} \quad \ldots (2)$$

$$X_{stream}^{t+1} = X_{stream}^{t} + \mathrm{rand} \times \mathrm{C} \times \left(X_{River}^{t} - X_{stream}^{t}\right) \quad \ldots (3)$$

$$X_{River}^{t+1} = X_{River}^{t} + \mathrm{rand} \times \mathrm{C} \times \left(X_{Sea}^{t} - X_{River}^{t}\right) \quad \ldots (4)$$

$$\left|X_{Sea}^{t} - X_{River}^{t}\right| < d_{max}, t = 1,2,\cdots,N_{sr} - 1 \quad \ldots (5)$$

$$d_{max}^{t+1} = d_{max}^{t} - d_{max}^{t}/t_{max} \quad \ldots (6)$$

$$X_{stream}^{'} = LB + \text{rand} \times (UB - LB) \quad \ldots (7)$$

Where, N_{pop} is number of members of the population; N_{stream}: The number of members representing the river in the population; N_{sr}: The number of members representing rivers and oceans in the population; N_{river}: The number of members representing the river in the population; t: Current iteration number; X_{stream}^{t}: The member variable representing the stream in the current iteration; X_{River}^{t}: Member variable representing the river in the current iteration; X_{Sea}^{t}: Member variables representing the ocean in the current iteration; C: A coefficient that varies linearly in the interval[1,2]; d_{max}: Condition of judgment; LB: Lower limit of population member variable; UB: Upper limit of population member variable; $X_{stream}^{'}$: Stream member vector updated in the current iteration

Improved Water Cycle Algorithm (IWCA)

Considering any single promotion strategy cannot comprehensively improve the whole performance of the optimization algorithm, multiple strategies are introduced at the same time. The elite memory strategy, the population chaotic mutation strategy and the population reconstruction strategy were introduced to establish an improved water cycle algorithm. Among the three improvement strategies, the elite memory strategy helps to balance the ability of exploitation and exploration, while the population chaotic mutation strategy and the population reconstruction strategy can improve the global optimization ability and avoid getting trapped by the local optimization. The above mentioned improvement strategies are described in detail as follows:

(1) A movement strategy inspired by PSO

PSO has good search capabilities because the guidance strategy of elite memory is applied to the movement strategy of each iteration of PSO[20,21]. The movement strategy based on the improved PSO is described as Eqs. 8 and 9[ref. 9], through which each particle agent updates its position vector. After IWCA's movement strategy updates each position vector of the population, another movement strategy inspired by PSO is used to update each position vector of the population. This step can effectively improve the search capabilities of WCA.

$$v_i^d(k+1) = \omega \cdot v_i^d(k) + c_3 \cdot r_4 \cdot \left(x_{pb}{}^d(k) - x_i^d(k)\right) + c_4 \cdot r_5 \cdot \left(x_{gb}{}^d(k) - x_i^d(k)\right) \quad \ldots (8)$$

$$x_i^d(k+1) = x_i^d(k) + v_i^d(k+1) \quad \ldots (9)$$

Where, ω is a constant in [0,1], c_3 and c_4 are coefficients generated from [0,2],r_4,r_5 are random variables in [0,1], x_{gb} means the global best position in current iteration, x_{pb} means personal best position in current iteration, $\text{i} = 1, \cdots, \text{N}$.

(2) A movement strategy based on chaotic mutation operator

The chaotic mutation operator overcomes the problems caused by randomness and improves the ability to avoid local convergence or premature maturity. In the literature[22], ten chaotic maps are proposed but here the sine chaotic map is selected as a kind of chaotic map. The movement strategy of the population can be described in Eq. 10.

$$x_i(k+1) = a \cdot x_i^2(k) \cdot sin\left(\pi \cdot x_i(k)\right) \quad \ldots (10)$$

Where, a = 2.3, $i = 1, \cdots, N$.

When each position vector of the population is updated by Eq. 10, a new position vector will be obtained. By comparing the objective function value of each position vector with that of the new position, the one with smaller objective function value will be kept in the position vectors of the population. The whole process of the hybrid algorithm is described in Figure 1.

(3) Population reconstruction strategy

The procedure of the population reconstruction strategy is shown in Figure 2, and the details are as follows:

Step 1: Generate each individual in Population 1 through the Opposition Based Learning (OBL)[7], and obtain a new population (Population 2).

Step 2: Perform Chaotic Mutation (CM)[8] on each individual of Population 1 and Population 2, respectively, and obtain two new chaotic sequences, namely Population 3 and Population 4.

Step 3: Combine Population 1, Population 2, Population 3 and Population 4 into a group, and calculate the objective function value of each individual.

Step 4: Sort all individuals by the minimum value, and select the top 25 % of individuals to form a new population.

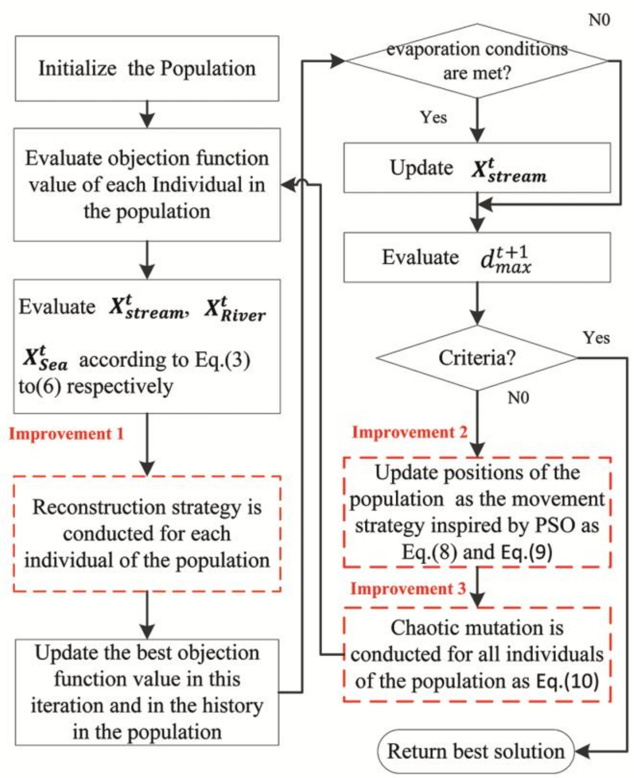

Fig. 1 — The flowchart of IWCA

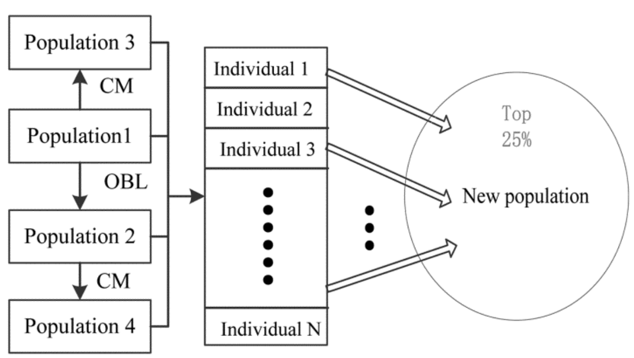

Fig. 2 — The procedure of reconstruction strategy

Optimized performance test using improved water cycle algorithm

In order to verify that the optimization performance of IWCA is better than that of WCA, 13 benchmark functions[23] proposed in Table 1 are tested using WCA and IWCA respectively as shown in Table 1. Each test is repeated 30 times independently. In these tests, the overall scale is 30, the total number of iterations is 500, and the dimensions of F1 to F13 are 30. Other settings of WCA and IWCA are as follows: the initial coefficients of WCA, IWCA are set following Eskandar *et al*.[19].

The 13 test function results of the three algorithms of PSO, WCA and IWCA are compared and listed in Table 2. In Table 2, 'fmin' means the best value of each benchmark function. The closer the benchmark function value is to 'fmin', the better the benchmark function value is. By the results in Table 2, except PSO is better for F2, WCA is better for F6 and PSO is better for F10 compared to IWCA, it is seemed that the optimization performance of IWCA is better than that of PSO by best value of 11 to 2, while the optimization performance of IWCA is better than that of PSO by best value of 13 to 0. Any single improvement strategy will improve one performance of the algorithm while it probably reduces the performance of the algorithm in other aspects. Therefore, multiple improvement strategies are helpful to comprehensively improve the optimization performance of the algorithm.

Therefore, the comparison proves that the optimization performance of IWCA has been improved on the basis of WCA which indicates the effectiveness of the improvement strategy, and the optimization performance of IWCA is better than that of PSO and WCA.

Fault diagnosis model based on improved water cycle algorithm and LSSVM classifier

LSSVM classifier

The Least Square Support Vector Machine (LSSVM) algorithm is developed from the Support Vector Machine (SVM) algorithm. The LSSVM algorithm trains the input and output of the training sample to find a proper functional relationship, and uses an optimization method to search for the optimal parameters which will give rise to the functional relationship with the smallest fitting error. Therefore, the LSSVM algorithm can be used to solve the classification problem with the calculation steps shown below:

Step 1: Determine the training sample and model organization. $\{ (c_j, r_j)/c_j \in R, r_j \in R^m, j=1,2,...M\}$ is the training sample set, where c_j, r_j are the output and input of the training sample, M is the number of training samples, m is the input dimension. The functional relationship between sample input and output can be described as:

$$c_j = P^T f(r_j) + a \quad \dots (11)$$

Where, P represents the unit normal vector of the hyperplane, a represents the distance from the origin to the hyperplane, and *f(·)* represents the nonlinear mapping function.

Step 2: Determine the nonlinear function which can describe the relationship between the input and output of the sample. In this paper, the Gaussian kernel function is selected as the nonlinear function relationship of the LSSVM model with the expression presented as follows:

$$Gauss(r_j, r_l) = \left(1/_{\sigma^2}\sqrt{e} \right)^{\|r_j - r_l\|^2} \quad \ldots (12)$$

Where, σ is the width constant of the nuclear parameter.

Step 3: optimization of σ and γ parameter. When the Gaussian kernel function is selected as the sample input and output nonlinear function relationship, it is necessary to use the training sample to determine a set of parameters σ and γ to minimize the fitting accuracy of the LSSVM model. Therefore, the fitting process of the LSSVM model becomes a parameter optimization process. Eq. 13 is the objective function and constraint conditions of LSSVM model parameter optimization.

$$\begin{cases} \min obj = \|P\|^2 + \gamma \sum_{j=1}^{M} e_j^2 \\ s.t. \begin{cases} e_j = \left(P^T f(r_j) + a\right) - c_j \\ e_j \geq 0, \ j = 1,2,\cdots M \end{cases} \end{cases} \quad \ldots (13)$$

Table 1 — Benchmark functions for testing

Function	Range
$F_1(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10,10]
$F_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	[-100,100]
$F_4(x) = \max_i \{\lvert x_i \rvert, 1 \leq i \leq n\}$	[-100,100]
$F_5(x) = \sum_{i=1}^{n-1} \left[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2 \right]$	[-30,30]
$F_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	[-100,100]
$F_7(x) = \sum_{i=1}^{n} i \cdot x_i^4 + random[0,1)$	[-1.28,1.28]
$F_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	[-500,500]
$F_9(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(2\pi x_i) + 10\right]$	[-5.12,5.12]
$F_{10}(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	[-32,32]
$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i-1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600,600]
$F_{12}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_1 - 1)^2[1 + sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_{i+1}}{4},\ u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a) & x_i < -a \end{cases}$	[-50,50]
$F_{13}(x) = \frac{1}{10}\left\{sin^2(3\pi x_i) + \sum_{i=1}^{n}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	[-50,50]

Table 2 — Test results of 13 benchmark functions

F	fmin		PSO	WCA	IWCA
F1	0	Ave	7.11e-5	1.15e-5	9.337e-6
		Std	8.35e-5	3.783e-5	1.534e-5
F2	0	Ave	2.59e-4	2.5040	0.0531
		Std	9.74e-5	5.4997	0.0229
F3	0	Ave	196.36	122.63	18.773
		Std	68.371	62.89	25.369
F4	0	Ave	3.691	18.887	0.6651
		Std	0.7158	5.005	1.0617
F5	0	Ave	59.376	242.403	0.3591
		Std	44.397	662.82	0.2587
F6	0	Ave	4.89e-5	1.11e-5	3.07e-5
		Std	9.58e-5	3.418e-5	5.995e-4
F7	0	Ave	0.0267	0.6786	0.01753
		Std	0.0184	0.2848	0.4193
F8	-12569	Ave	-6769.3	-8007.4	-8362.3
		Std	807.091	744.58	544.37
F9	0	Ave	55.92	106.165	47.633
		Std	22.419	27.435	12.479
F10	0	Ave	0.00135	7.0250	0.6557
		Std	0.0033	4.318	0.5821
F11	0	Ave	0.0237	0.0408	0.00945
		Std	0.0215	0.0330	0.0143
F12	0	Ave	0.00978	1.1064	5.02e-4
		Std	0.0157	1.5687	1.68e-3
F13	0	Ave	0.0066	0.0427	0.00489
		Std	0.0043	1.5687	0.00617

Where, e_j is the fitting error of the j-th input and output samples, and γ is the error penalty factor.

Step 4: Obtain the LSSVM regression model. The LSSVM regression model can be obtained by using the optimized parameters σ and γ as the model parameters. The model is expressed as follows:

$$L(r) = \sum_{j=1}^{M} A_j \cdot Gauss(r_j, r) + a \qquad \dots (14)$$

Where, A_j is a constant coefficient vector.

Step 5: LSSVM classification calculation. Substitute the calculated value $L(r)$ of the LSSVM classification model into the sign function to obtain sign($L(r)$) and determine the sample category according to sign($L(r)$).

LSSVM classifier parameter optimization

The steps of parameter optimization process using the IWCA-based LSSVM model are as follows:

Step 1: Determine the training set and test data set required for LSSVM model training, and divide the input data and output data in the training set and test set.

Step 2: Generate an initial population in the IWCA algorithm, use the penalty coefficient γ and the kernel function σ as decision variables. At last, the composition vector of each member of the population is composed of decision variables.

Step 3: Use IWCA to obtain the optimized penalty coefficient γ and the kernel function σ.

Step 4: The IWCA algorithm judges whether the end condition is met, and the iterative calculation ends when the condition is met, otherwise, continue to step 3. In this paper, the end condition is that the calculation error of test value in LSSVM classifier is less than the set value.

Decision fusion strategy using LSSVM classifier group

In order to make full use of the feature information in the time-frequency domain and ensure that each sub-classifier can achieve complementary advantages, the classification results of each sub-classifier are merged using an ensemble algorithm based on the evaluation matrix. The basic idea is: use a confusion matrix to measure the recognition ability of each classifier for each type of fault, and adaptively assign decision weights to each classifier according to the preliminary diagnosis, and finally make full use of training information to improve the accuracy of classification decision.

Fault diagnosis method based on IWCA and LSSVM

For the remote power supply system in CUINs, the fault diagnosis can be completed based on IWCA and LSSVM according to the following steps:

(1) First, divide the submarine composite cable of the remote supply system into regions, and collect the current and voltage signals in each division.
(2) Use the EMD method to extract features of the collected signals.
(3) Optimize the parameters of each sub-classifier in the LSSVM classifier group.
(4) Use the fusion strategy to evaluate all sub-classifier decisions and obtain the final diagnosis result.

Simulation and analysis

The remote power supply system in cable-based underwater information network is mainly composed of Shore Power Feeding Equipment (SPFE), Primary Node (Primary Node, PN) and submarine cables. All the above-mentioned parts assemble together to form the remote power supply system loop.

It can be seen from Figure 3 that two adjacent master nodes are connected by submarine composite cables. Consequently, cable faults can be easily judged based on the current changes in the cables between the two nodes. The whole judge steps include firstly, dividing the submarine composite cable of the remote supply system into sections; collecting the current value of each section and compare the current changes in the section before and after each sampling period; using the IWCA and LSSVM fault diagnosis models to diagnose and obtain the diagnosis result. After dividing the intervals of the constant current remote supply system, each interval can be regarded as composed of an equivalent RLC loop whose equivalent circuit is presented in Figure 4[ref. 24].

As shown in Figure 4, there are six intervals in the simulation experiment, namely $j = 6$. The length of the submarine cable in the interval is 30 km, the equivalent inductances L1 – L6 are all 20 mH, the equivalent capacitances C1 – C7 are 7.2 μF, and the equivalent resistances R1 – R6 are all 30 Ω. It is assumed that the shore-based output current of the constant current remote supply system is 1.5 A.

According to the 6-segment interval model in Figure 4, the corresponding training data can be obtained. After the parameters of the LSSVM classifier are optimized, the fault diagnosis method is obtained and used to analyze the data in Table 3. In LSSVM classifier optimized by IWCA which is trained by data

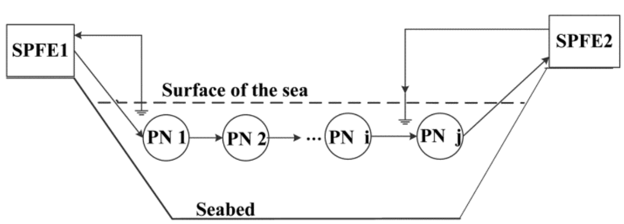

Fig. 3 — Structure diagram of multi-node constant current remote supply system

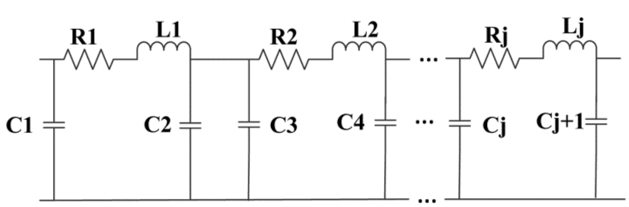

Fig. 4 — Constant current remote supply cable model

Table 3 — Equivalent values of field currents at each PN short-circuit faults occurs before and immediately

Range	1	2	3	4	5	6
before	1.505	1.497	1.512	1.502	1.509	1.507
after	1.551	1.554	1.560	1.432	1.433	1.439

of cable fault, each classifier means that there is a fault in a section of the line corresponding to the classifier. Therefore, a conclusion that there is an open circuit fault in interval 4 is obtained by model calculation including modelling and LSSVM classifier. Based on the experimental results, the proposed fault diagnosis method has a good diagnosis rate for the constant current remote supply system. Because parts of the training process can be performed offline, the operating efficiency is greatly improved and calculation costs get reduced. Therefore, the proposed fault diagnosis method is proved to be suitable for fault diagnosis of submarine cable systems. What is more, the proposed diagnosis method has great possibility of being successfully applied into solving other problems involving into underwater observation network such as the underwater manipulation[25], system control[26], etc.

Conclusions

This paper proposed a new fault diagnosis method for the constant current remote power supply system in CUINs based on the Improved Water Cycle Algorithm (IWCA) and the LSSVM multi-classifier group. The improved IWCA algorithm is developed based on the WCA algorithm by combining chaotic mutation strategy, the elite memory strategy and the population reconstruction strategy. At last, the effectiveness of the new fault diagnosis method is verified by simulation experiments.

Acknowledgments

This work is supported by Hubei Provincial Natural Science Foundation for Innovation Groups (No. 2021CFA026）and the Open Foundation of the State Key Laboratory of Fluid Power and Mechatronic Systems (under Grant GZKF-202001), in part by the Fundamental Research Funds for the Central Universities (under Grant 2021XJJS016).

Conflict of Interest

There is no conflict of interest.

Author Contributions

MJZ: Resources, Methodology and Writing-review and editing; GX: Simulation and analysis, Writing original draft, and data processing; SH: Writing—review and editing.

References

1 Task Force for the Research on China's Engineering Science and Technology Development Strategy 2035 Marine Research Group, Development strategy for China's marine engineering science and technology to 2035. *Eng Sci*, 19 (2017) 108–117.

2 Chen Y H, *Research on the key technologies of power junction for cabled ocean observatories system based on tree topology*, Hangzhou: Zhejiang University, 2012, pp. 23–38.

3 Taylor S M, Transformative ocean science through the VENUS and NEPTUNE Canada ocean observing systems, *Nucl Instrum Methods Phys Res A: Accel Spectrom Detect Assoc Equip*, 602 (2009) 63-67.

4 Kawaguchi K, Kaneda Y & Araki E, The DONET: A real-time seafloor research infrastructure for the precise earthquake and tsunami monitoring, *Proceeding of OCEANS 2008 - MTS/IEEE Kobe Techno-Ocean*, 2008, Kobe, Japan.

5 Lin F, Xiao X Y, Li G D, Probabilistic fault localization method considering voltage measurement errors, *Power Syst Technol*, 39 (2015) 3592–3597.

6 Feng Y B, Li Z G & Wang X H, Open-circuit fault identification and interval locating method of optoelectric cable of seafloor observatory network, *Automation of Electric Power Systems*, 39 (2015) 151–156.

7 Aguzzi J, Chatzievangelou D, Francescangeli M, Marini S, Bonofiglio F, *et al.*, The Hierarchic Treatment of Marine Ecological Information from Spatial Networks of Benthic Platforms, *Sensors*, 20 (2020) p. 1751.

8 Zhang Z, Zhou X J, Wang X C & Wu T S, Research on High-Impedance Fault Diagnosis and Location Method for Mesh Topology Constant Current Remote Power Supply Systemin Cabled Underwater Information Networks, *IEEE ACCESS*, 7 (2019) 88609-88621.

9 Wang L, Zhou X J & Zhang Z, Design and Analysis of an Equivalent Load Power-Stability Control Circuit for Cabled underwater Information Networks, *IEEE ACCESS*, 8 (2020) 158549–158558.

10 Jouhari M, Ibrahimi K, Tembine H & Ben Othman J, Underwater Wireless Sensor Networks: A Survey on Enabling Technologies, Localization Protocols, and Internet of Underwater Things, *IEEE ACCESS*, 7 (2019) 96879-96899.

11 Zhang Z, Zhou X J, Wang X C & Wang L A, Novel Diagnosis and Location Method of Short-Circuit Grounding High-Impedance Fault for a Mesh Topology Constant Current Remote Power Supply System in Cabled Underwater Information Networks, *IEEE ACCESS*, 7 (2019) 121457-121471.

12 Zhang Y J, Wang X J, Luo Y P, Xu Y, He J H, *et al.*, A CNN Based Transfer Learning Method for High Impedance Fault Detection, (Power & Energy Society General Meeting (PESGM), 2020), IEEE, 2020, pp. 1-5.

13 Michael F, Wang Z & Fernandez-Gonzalez R, Learning to analyze in vivo microscopy: Support vector machines, *Biochim Biophys Acta Proteins Proteom*, 1865 (2017) 1719-1727.

14 Tian C & Han X, A study on ship collision conflict prediction in the Taiwan Strait using the EMD-based LSSVM method, *PloS One*, 16 (2021) e0250948.

15 Zhang K, Su J P, Sun S A, Liu Z X, Wang J R, *et al*., Compressor fault diagnosis system based on PCA-PSO-LSSVM algorithm, *Sci Prog*, 104 (2021) 368504211026110.

16 He C, Wu T, Liu C C & Chen T, A novel method of composite multiscale weighted permutation entropy and machine learning for fault complex system fault diagnosis, *Measurement*, 158 (2020) 107748.

17 Zhao Y P, Wang J J, Li X Y, Peng G J & Yang Z, Extended least squares support vector machine with applications to fault diagnosis of aircraft engine, *ISA Trans*, 97 (2020) 189-201.

18 Gao X J, Wei H F, Li T Y & Yang G L, A rolling bearing fault diagnosis method based on LSSVM, *Adv Mech Eng*, 12 (2020) 168781401989956.

19 Eskandar H, Sadollah A, Bahreininejad A & Hamdi M, Water cycle algorithm - A novel metaheuristic optimization method for solving constrained engineering optimization problems, *Comput Struct*, 110 (2012) 151-166.

20 Kennedy J & Eberhart R C, Particle Swarm Optimizer, In: *Proceedings of the IEEE International Conference on Neural Networks Perth*, (1995) pp. 1942–1948.

21 Xiang G & Xiang X B, 3D trajectory optimization of the slender body freely falling through water using cuckoo search algorithm, *Ocean Eng*, 235 (2021) p. 109354.

22 Tian T, Liu C, Guo Q, Yuan Y, Li W, *et al*., An improved ant lion optimization algorithm and its application in hydraulic turbine governing system parameter identification, *Energies*, 11 (2018) p. 95.

23 Tang K, Yao X, Suganthan P N, Mac Nish C, Chen Y-P, *et al*., Benchmark Functions for the CEC' 2008 Special Session and Competition on Large Scale Global Optimization, (University of Science and Technology of China (USTC), School of Computer Science and Technology, Nature Inspired Computation and Applications Laboratory (NICAL)), Héféi, Anhui, China, Tech Rep, 2007.

24 Geng K & Feng L, Fault location of submarine cable in power system of submarine observation network based on PCA/LSTM, *J Ocean Technol*, 39 (2020) 22-29.

25 Zhang Q, Zhang J L, Chemori A & Xiang X B, Virtual Submerged Floating Operational System for Robotic Manipulation, *Complexity*, 2018 (2018) 1–18.

26 Wang Z, Yang S L, Xiang X B, Vasilijevic´ A, Miškovic´ N, *et al*., Cloud-based mission control of USV fleet: architecture, implementation and experiments, *Control Eng Pract*, 106 (2021) p. 104657.