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Supercapacitor module quality prewarning based on the improved whale optimization algorithm and GM (1,1) gray prediction model

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Abstract: This paper proposes an algorithm combining the improved whale optimization algorithm (WOA) and GM (1,1) to predict the number of qualified products in the test batches of supercapacitor modules. Based on this algorithm, a quality prewarning system is developed on LabVIEW software. First, the GM (1,1) gray prediction model is established with the number of qualified products in the test batch as the original sequence, and then a nonlinear iterative parameter is proposed to improve the WOA. The improved WOA is used to optimize the background value sequence in the GM (1,1) gray prediction model, to obtain the optimal prediction algorithm. Then, on the LabVIEW software platform, the simulation of the GM (1,1) gray prediction model, the algorithm combining WOA and GM (1,1) and the algorithm combining the improved WOA and GM (1,1) are carried out for fifty groups of original data series. Taking one group of simulation data results as an example, the relative error of the prediction value of the algorithm combining the improved WOA and GM (1,1) is 0.0004%, which is better than 0.0112% of the algorithm combining the WOA and GM (1,1) and 1.5429% of the GM (1,1) gray prediction model. Finally, the quality prewarning system of the supercapacitor module is developed by using LabVIEW software, which provides a more accurate quality prewarning function for the test process of the supercapacitor module.

Keywords: GM (1,1) gray prediction model, whale optimization algorithm (WOA), background value optimization, LabVIEW, quality prewarning

1. INTRODUCTION

As a high energy storage capacitor, a supercapacitor has the characteristics of high power density, short charging and discharging time, long cycle life, wide operating temperature range, etc. It has great application value and market potential in industrial control, transportation, new energy vehicles and many other fields (Yu, 2015). According to the energy storage principle of carbon-based supercapacitors, the monomer voltage is generally approximately 2.7 V (Ling, 2018). To meet the requirements of a 5 V standby power supply in the circuit, two monomer capacitors are often used as a capacitor module in series. Because the supercapacitor module is a small electronic component, it is suitable to use automatic batch detection when testing its parameters before leaving the factory. Due to the development of industrial automation, an increasing number of supercapacitor companies are setting up automated measurement and control platforms and controlling the testing equipment according to predetermined procedures to complete the expected testing tasks. It is mainly composed of sensors, PLCs, industrial control computers, industrial control software and other parts (Chen, 2021). A large amount of data has been accumulated in the test process. How to use these generated batch test data to prewarn the quality of future products in the process of automatic testing is an important issue.

The problem of quality prewarning of supercapacitor modules is actually based on the prediction of test data. The GM (1,1) gray prediction model has no strict requirements for sample size and data distribution. Its principle is simple, and its applicability is strong. It is characterized by good prediction without a large amount of time series data. Gao applied the gray prediction model to predict the service life of shaft parts more accurately (Gao, 2014). Ding et al. predicted and analyzed the development trend of the number of private hospitals, beds and doctors in China from 2020 to 2025 by building a GM (1,1) gray prediction model (Ding, 2021). However, the GM (1,1) gray prediction model is mainly applicable to situations where the prediction parameters grow quickly and steadily. In the quality prediction control of supercapacitor series modules, the prediction parameters are unstable, so the application of the GM (1,1) gray prediction model will be limited to a certain extent. Zhang et al. proposed using a parameter to modify the background value calculation formula in the GM (1,1) gray prediction model (Zhang, 2001). Luo et al. proposed using the first-order linear differential equation to reduce the simulation error caused by the background value construction formula in the GM (1,1) gray prediction model (Luo, 2003).

However, the GM (1,1) prediction model uses the same background value parameters for real-time change test data, which cannot fully reduce the prediction error of the model. Yang and Bi proposed a gray model based on particle swarm optimization, which can better improve the accuracy of medium- and long-term load forecasting of power systems (Yang, 2011). Zhang et al. designed a fault prediction model combining the traditional gray prediction model and the improved gray wolf algorithm to predict spindle faults in CNC machine tools (Zhang, 2022). Mirjalili et al., inspired by the social behavior of humpback whales, proposed a metaheuristic optimization algorithm, the whale optimization algorithm

(WOA) (Mirjalili, 2016). Chiu et al., through a calculation experiment and comparison of 14 benchmark continuous optimization problems, concluded that the periodic dynamic adjustment strategy has better performance than the decreasing or increasing strategy (Chui, 2018). Feng et al. improved the global search and local optimization performance of the whale optimization algorithm by introducing nonlinear time-varying adaptive weights (Feng, 2020).

Based on the above research, this paper proposes an algorithm combining the improved WOA and GM (1,1), which is used for the quality prewarning of supercapacitor modules. First, a nonlinear iteration factor is proposed to replace the linear iteration factor in the WOA to improve its optimization performance. Then, the improved WOA is used to optimize the background value sequence in the GM (1,1) gray prediction model, and the optimal prediction model is established. Then, the superiority of the algorithm combining the improved WOA and GM (1,1) is verified by simulations on the LabVIEW software.

The rest of this paper is organized as follows. The next section introduces the automatic test platform of supercapacitor series modules. Based on LabVIEW software, a quality prediction prewarning system for supercapacitor modules is developed. Finally, we draw a conclusion.

2. ESTABLISHMENT OF GM (1,1) GRAY PREDICTION MODEL

The GM (1,1) gray prediction model is a model that reveals the continuous development and change of things in the system. It is generally established for discrete series, and the discrete function needs to meet the smoothness condition. If the discrete series is not a smooth discrete function, it needs to be generated by one or more accumulations until the generated series is a smooth discrete function, and then the gray prediction model is used for modeling. The specific steps are as follows.

Set the original sequence:

$$X^{(0)} = (X^{(0)}(1) \quad X^{(0)}(2) \quad \cdots \quad X^{(0)}(n)) \tag{1}$$

Number sequence generated by accumulation:

$$X^{(1)} = (X^{(1)}(1) \quad X^{(1)}(2) \quad \cdots \quad X^{(1)}(n)) \tag{2}$$

where $X^{(1)}(1) = X^{(0)}(1)$, $X^{(1)}(2) = X^{(0)}(1) + X^{(0)}(2)$, $X^{(1)}(3) = X^{(0)}(1) + X^{(0)}(2) + X^{(0)}(3)$……

The gray difference equation is established, and the sequence of background values is generated from the immediate mean value of the sequence $X^{(1)}$:

$$Z^{(1)} = (Z^{(1)}(1) \quad Z^{(1)}(2) \quad \cdots \quad Z^{(1)}(n)) \tag{3}$$

$Z^{(1)}(n)$ satisfies the following relationship:

$$Z^{(1)}(n) = pX^{(1)}(n-1) + (1-p)X^{(1)}(n) \tag{4}$$

where p is a random vector in $[0,1]$, general primary selection $p = 0.5$.

Establish a differential equation for $X^{(1)}(t)$:

$$\frac{dX^{(1)}(t)}{dt} + aX^{(1)}(t) = u \tag{6}$$

The parameter is listed as $\hat{a} = (a \quad u)^T$, where a is the development coefficient and u is the driving coefficient. Let

$$B = \begin{pmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{pmatrix} \tag{7}$$

$$Y = (X^{(0)}(2) \quad X^{(0)}(3) \quad \cdots \quad X^{(0)}(n))^T \tag{8}$$

According to the idea of the least square method, it can be concluded that

$$\hat{a} = (B^T B)^{-1} \times B^T \times Y \tag{9}$$

Refer to Equations (6) and (9). The solution of the differential equation of $X^{(1)}(t)$ is expressed as:

$$\hat{X}^{(1)}(n) = \left(X^{(0)}(1) - \frac{u}{a}\right) e^{-a(n-1)} + \frac{u}{a} \tag{10}$$

Refer to Equation (10). Calculate the value of the specified position and its previous position. By decreasing, the predicted value of the specified position can be obtained as:

$$\hat{X}^{(0)}(n) = \hat{X}^{(1)}(n) - \hat{X}^{(1)}(n-1) \tag{11}$$

The error of the predicted value is calculated, and the formula is expressed as:

$$\varepsilon^{(0)}(n) = \left| \frac{X^{(0)}(n) - \hat{X}^{(0)}(n)}{X^{(0)}(n)} \right| \tag{12}$$

3. OPITIMIZING THE GM (1,1) GRAY PREDICTION MODEL THROUGH THE IMPROVED WOA

In the practical application of the GM (1,1) gray prediction model, the corresponding prediction results are different with different p values, so it is necessary to select the optimal value of p (Ding, 2018). This paper selects the best p value by the improved WOA to reconstruct the background value sequence to obtain the best prediction model.

3.1 Establishment of mathematical model of the WOA algorithm

The WOA is a bionic intelligent optimization algorithm that simulates the unique foraging behavior of humpback whales in bubble nets. It assumes that the current optimal individual is prey, and other individuals in the group approach the optimal individual. The algorithm is mainly divided into three stages: search for prey, shrinking encircling mechanism and spiral updating position.

The search for prey is the process of whales randomly searching for food. The whales randomly search according to each other's positions, which corresponds to the global exploration stage of the algorithm. The search for prey behavior is represented by the following equations:

$$D = |CP_{rand} - P(t)| \tag{13}$$

$$P(t+1) = P_{rand} - AD \tag{14}$$

where t indicates the current iteration, A and C are coefficient vectors, P_{rand} is a random position vector chosen from the current population, P is the position vector, and $| \, |$ is the absolute value. The vectors A and C are calculated as follows:

$$A = 2\alpha r - \alpha \tag{15}$$

$$C = 2r \tag{16}$$

where r is a random vector in $[0,1]$, and α linearly decreases from 2 to 0 over the course of iterations. The vector a is calculated as follows:

$$\alpha = 2 - \frac{2t}{t_{max}} \tag{17}$$

where t_{max} is the maximum number of iterations. When $|A| \geq 1$, whales enter the stage of searching for prey, and the whales will search randomly according to their respective phase positions.

The bubble-net behavior of whales includes two mechanisms: shrinking encircling mechanism and spiral updating position. When $|A| < 1$, the whale individual will move toward the whale that is in the current optimal position.

The shrinking encircling mechanism is represented by the following equations:

$$D = |CP_{best} - P(t)| \tag{18}$$

$$P(t+1) = P_{best} - AD \tag{19}$$

where P_{best} is the position vector of the best solution obtained thus far.

In the spiral updating position stage, whales will swim and seek food in a spiral way while approaching the best whale individual, searching for the possible optimal solution between the whale individual and the best individual. The initial point of spiral updating is the position of the current whale individual, and the target end point is the position of the current best whale individual. The spiral updating position is represented by the following equations:

$$D^* = |P_{best} - P(t)| \tag{20}$$

$$P(t+1) = D^* e^{bl} \cos(2\pi l) + P_{best} \tag{21}$$

where D^* represents the distance between the current whale and the whale at the best position, b is a constant for defining the shape of the logarithmic spiral, and l is a random number in $[-1, 1]$.

The selection of the three stages of searching for prey, shrinking encircling mechanism and spiral updating position is determined by the probability factor θ and the vector $|A|$. When $\theta \geq 0.5$, enter the spiral updating position stage. When $\theta < 0.5$ and $|A| \geq 1$, enter the search for prey. When $\theta < 0.5$ and $|A| < 1$, enter the shrinking encircling mechanism.

3.2 Improved WOA algorithm

This paper improves the WOA algorithm by proposing a nonlinear iteration factor to replace the linear iteration factor in the WOA algorithm. The curve composition of the nonlinear iteration factor is as follows: two semi-ellipses with a short axis of 2 and a long axis of t_{max}, tangent to $(t_{max}/2, 1)$, taking the quarter elliptical arc located in the upper half of $[0, t_{max}/2]$ and the quarter elliptical arc located in the lower half of $(t_{max}/2, t_{max}]$. The nonlinear iterative factor is calculated as follows:

$$\alpha = \begin{cases} 1 + \sqrt{1 - \left(\dfrac{2t}{t_{max}}\right)^2} & 0 \leq t \leq \dfrac{t_{max}}{2} \\ 1 - \sqrt{1 - \left(\dfrac{2(t - t_{max})}{t_{max}}\right)^2} & \dfrac{t_{max}}{2} < t \leq t_{max} \end{cases} \tag{22}$$

The comparison of the nonlinear iterative factor of the improved WOA and the linear iterative factor of the WOA is shown in Fig. 1.

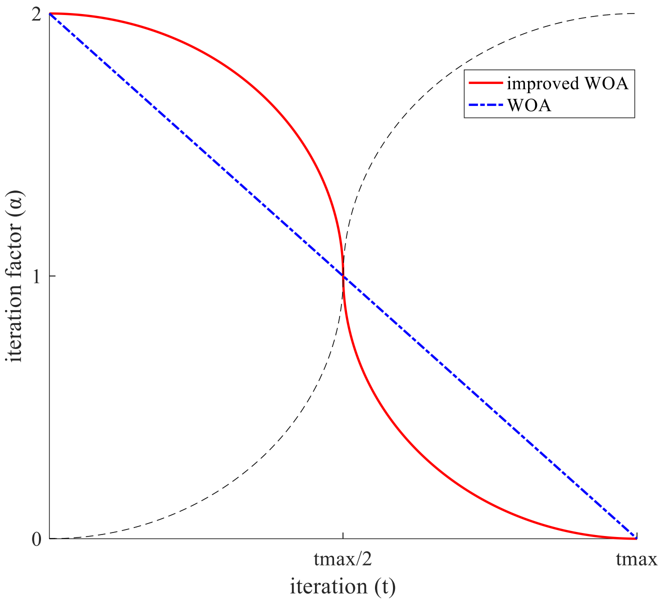

Fig. 1. Comparison of the nonlinear iteration factor of the improved WOA and the linear iterative factor of the WOA.

As shown in Fig. 1, at the beginning of the iteration, i.e., $t \in [0, t_{max}/2]$, the value of the nonlinear iteration factor decreases more slowly than the value of the linear iteration factor, which can expand the whale search range and maintain better search ability. In the later stage of iteration, when $t \in (t_{max}/2, t_{max}]$, the value of the nonlinear iteration factor decreases more quickly, which can achieve higher optimization accuracy. In other words, the proposed nonlinear iteration factor improves the algorithm's global exploration and local development capabilities at different stages.

The pseudocode of the algorithm combining the improved WOA and GM (1,1) is adapted from (Mirjalili, 2016) and presented in Fig. 2.

Initialize the whale population P_i (i =1, 2, …, n)
Initialize the position vector $P(1)$=0.5
P_{best} = the best search agent
***while** (t < maximum number of iterations)*
  ***for** each search agent*
  Update α by the Eq. (22)
  Update A, C, l, and θ
    ***if1** (θ<0.5)*
      ***if2** (|A|<1)*
        Update the position of the current search by the Eq. (19)

else ***if2*** *(|A|≥1)*
Select a random search agent (P_{rand})
Update the position of the current search by the Eq. (14)
end if2
else ***if1*** *(θ≥0.5)*
Update the position of the current search by the Eq. (21)
end for
calculate the fitness of each search agent by the Eq. (12)
update P_{best} if there is a better solution
t=t+1
end while
return P_{best}

Fig. 2. Pseudocode of the algorithm combining the improved WOA and GM (1,1).

4. SIMULATION AND DISCUSSION

In the process of the supercapacitor module test, ninety-eight supercapacitor modules are detected in each batch. Due to the error of the test instrument and the fact that there are unqualified products in the test process, the predicted number of qualified products is ninety-one or more, which is considered reasonable.

Considering that the GM (1,1) gray prediction model does not need a large number of time series to make a good prediction, the quantity of qualified products in the last five batches is taken as the original number series of the GM (1,1) gray prediction model. The improved WOA is used to optimize the p value in the GM (1,1) model, reconstruct the background value sequence, and predict the quantity of qualified products in the next batch of the supercapacitor module. Because the relative error needs to be compared between the predicted value and the actual test value, the relative error obtained by comparing the predicted value of the fifth batch with the actual value is the adaptive degree function calculated by the algorithm. If the predicted quantity of qualified products is lower than the set value, the system will automatically send a prewarning to remind the operator or engineer to check whether the equipment operates normally and whether there are problems in the preparation process of the supercapacitor module. The purpose of this is to prevent the occurrence of too many unqualified products in advance.

The simulation experiment of the quality prewarning algorithm is carried out in the LabVIEW software environment. The simulation randomly generates a sequence consisting of five random integers between ninety-one and ninety-eight as the original sequence of the GM (1,1) gray prediction model, the algorithm combining the WOA and GM (1,1) and the algorithm combining the improved WOA and GM (1,1). The value of p is initialized to 0.5, the maximum number of iterations t is 30, the logarithmic spiral shape constant b is 1, and the whale population is 1. The program uses the for loop to obtain fifty groups of relative errors of the above three algorithms in fifty cycles. The prediction and relative errors of one group of simulation experiments are shown in Tab. 1. The relative errors of fifty groups of simulation experiments are shown in Tab. 2, and their relative error curves are shown in Fig. 3.

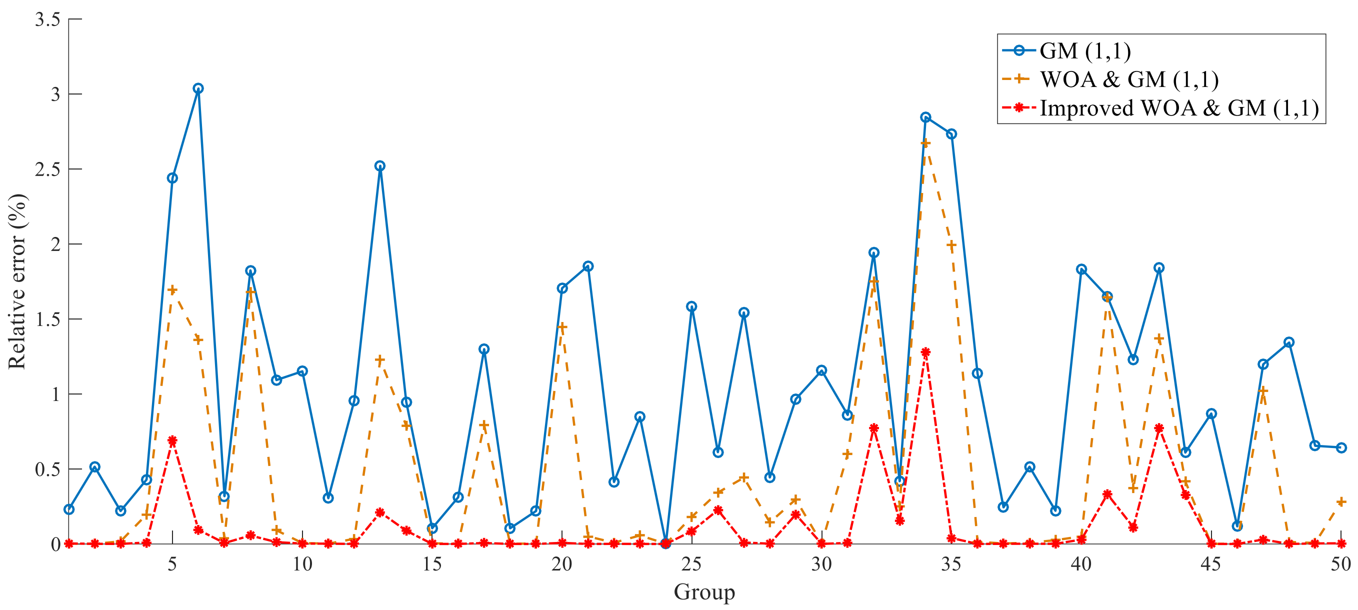

Fig. 3. Relative error curve of simulation experiments of GM (1,1), WOA & GM (1,1), and improved WOA & GM (1,1).

Table 1. Prediction and relative error of one group simulation experiment of GM (1,1), WOA & GM (1,1), and improved WOA & GM (1,1).

Time series	Original sequence	GM (1,1)		WOA & GM (1,1)		Improved WOA & GM (1,1)	
		Prediction	Relative error	Prediction	Relative error	Prediction	Relative error
1	92	92	N/A	92	N/A	92	N/A
2	97	95.4423	1.6059%	96.9724	0.2844%	96.9610	0.0402%
3	92	93.7934	1.9493%	95.2893	3.5753%	95.2782	3.5632%
4	91	92.1733	1.2890%	93.6355	2.8961%	93.6246	2.8841%
5	92	90.5806	1.5429%	92.0103	0.0112%	91.9996	0.0004%

Table 2. Relative error (%) of simulation experiments of GM (1,1), WOA & GM (1,1), and improved WOA & GM (1,1).

Group	GM (1,1)	WOA & GM (1,1)	Improved WOA & GM (1,1)	Group	GM (1,1)	WOA & GM (1,1)	Improved WOA & GM (1,1)
1	0.2298	0.0029	0.0034	26	0.6119	0.3427	0.2264
2	0.5150	0.0012	0.0009	27	1.5429	0.4418	0.0097
3	0.2197	0.0174	0.0006	28	0.4433	0.1436	0.0019
4	0.4290	0.1965	0.0095	29	0.9654	0.2972	0.1965
5	2.4379	1.6931	0.6928	30	1.1560	0.0047	0.0006
6	3.0355	1.3611	0.0938	31	0.8601	0.5990	0.0068
7	0.3186	0.0371	0.0061	32	1.9410	1.7502	0.7737
8	1.8233	1.6770	0.0567	33	0.4183	0.2530	0.1530
9	1.0924	0.0914	0.0123	34	2.8459	2.6730	1.2793
10	1.1509	0.0061	0.0026	35	2.7317	1.9932	0.0398
11	0.3048	0.0022	0.0022	36	1.1349	0.0149	0.0001
12	0.9558	0.0344	0.0001	37	0.2442	0.0030	0.0012
13	2.5203	1.2277	0.2107	38	0.5148	0.0083	0.0017
14	0.9470	0.7888	0.0885	39	0.2214	0.0254	0.0010
15	0.1049	0.0045	0.0004	40	1.8335	0.0505	0.0294
16	0.3111	0.0012	0.0002	41	1.6485	1.6426	0.3318
17	1.2984	0.7919	0.0064	42	1.2269	0.3742	0.1111
18	0.1045	0.0008	0.0004	43	1.8391	1.3715	0.7715
19	0.2199	0.0036	0.0001	44	0.6092	0.4169	0.3257
20	1.7045	1.4471	0.0073	45	0.8696	0.0005	0.0003
21	1.8535	0.0505	0.0001	46	0.1172	0.0018	0.0001
22	0.4132	0.0084	0.0008	47	1.1974	1.0199	0.0299
23	0.8462	0.0569	0.0002	48	1.3427	0.0135	0.0001
24	0.0047	0.0015	0.0001	49	0.6543	0.0067	0.0036
25	1.5831	0.1818	0.0858	50	0.6432	0.2820	0.0045

The experimental data in Tab. 1 show that when the original sequence is $(92 \quad 97 \quad 92 \quad 91 \quad 92)$, the relative error between the predicted value and the actual value of the number of qualified products in the fifth sequence of the algorithm combining the improved WOA and GM (1,1) is 0.0004%, which is better than the relative error of the algorithm combining the WOA and GM (1,1) of 0.0112% and the relative error of the GM (1,1) gray prediction model of 1.5429%. Tab. 2 and Fig. 3 show the simulated relative error values and curves of the three algorithms for fifty groups of random original sequences in LabVIEW software. It can be seen that in each group, the relative error of the predicted value of the algorithm combining the improved WOA and GM (1,1) is significantly smaller than that of the algorithm combining the WOA and GM (1,1) and the GM (1,1) gray prediction model.

The simulation results clearly show that the algorithm combining the improved WOA and GM (1,1) has higher prediction accuracy in the quantity prediction of qualified products of supercapacitor modules.

5. PRACTICAL APPLICATION

5.1 Supercapacitor module test platform

To realize the automatic test of the parameters of the supercapacitor module, an automatic test platform is established, as shown in Fig. 4. The automatic test platform is jointly controlled by two PLCs. The Omron CP1H-XA40DT-D PLC is used to test the main performance parameters of the supercapacitor module and store them in the designated register address of the PLC. The Omron CP1E-40DT-D PLC is used for automatic control, which mainly controls the movement of the material tray carrying ninety-eight supercapacitor modules at each station and screens out the unqualified supercapacitor modules.

The main test process of the automatic test platform is as follows: when the equipment is started, the feeding cylinder pushes the material tray into the voltage test station, and the voltage test station clamps the supercapacitor module and performs the voltage test. After the voltage test, the servo mechanism sends the material tray to the next station for the internal resistance test. After the internal resistance test, the unqualified products are automatically screened, and then the supercapacitor module is discharged automatically.

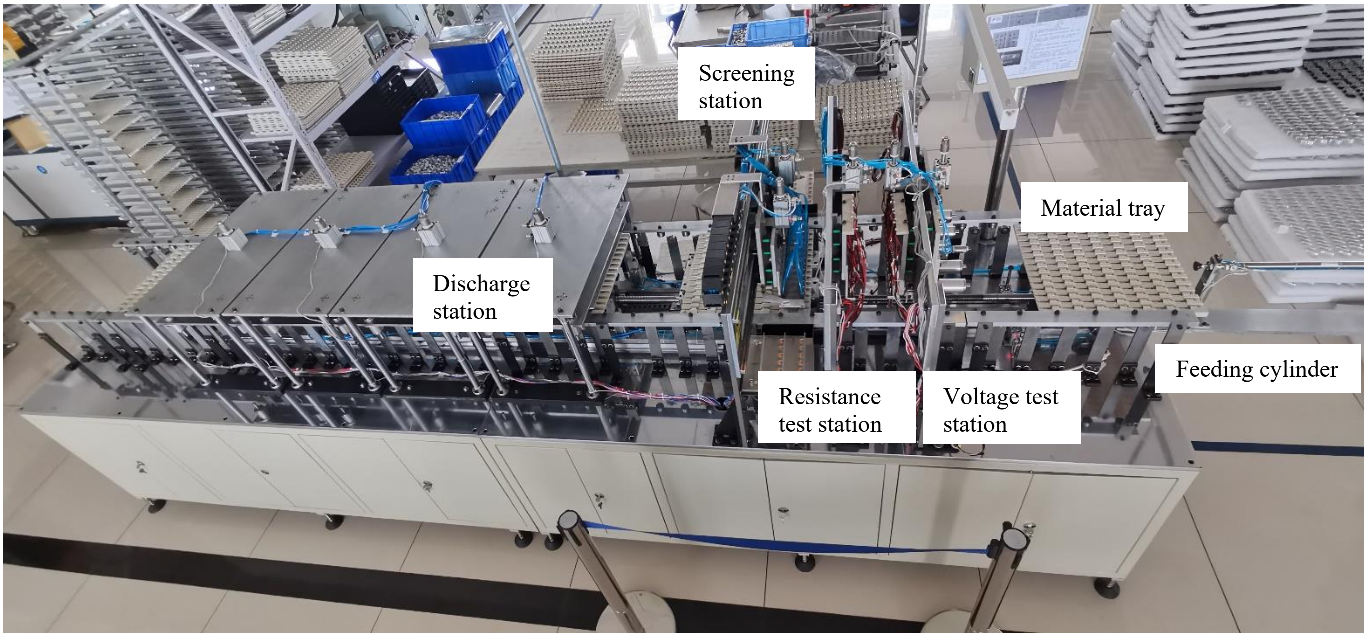

Fig. 4. Automatic test platform for supercapacitor module.

5.2 Quality prewarning program developed in LabVIEW

Test data storage, monitoring, and quality prewarning of the implemented quality prewarning system are developed in LabVIEW software. Fig. 5 depicts a program flowchart, which describes the operation sequence executed in the quality prewarning system of the supercapacitor module.

The quality prewarning system program uses OPC technology to realize communication between the LabVIEW software and the PLC (Liu, 2015) and uses NI OPC servers to establish the link relationship between the register address in the PLC and the LabVIEW software (Qiao, 2005). Due to the large amount of data detected, this paper selects the SQL Server database as the platform for detecting data storage. This paper uses UDL to connect to the database (Cai, 2020), and the implementation process is as follows: Open the LabVIEW program, create a new VI, click create data link in the tools column of the front panel to pop up the data link properties window, select Microsoft OLE DB provider for SQL Server in the provider column, configure the relevant information connected to the SQL Server database in the connection column, and save the UDL file. After the UDL is created, relevant operations can be performed on the database through the database toolkit in LabVIEW.

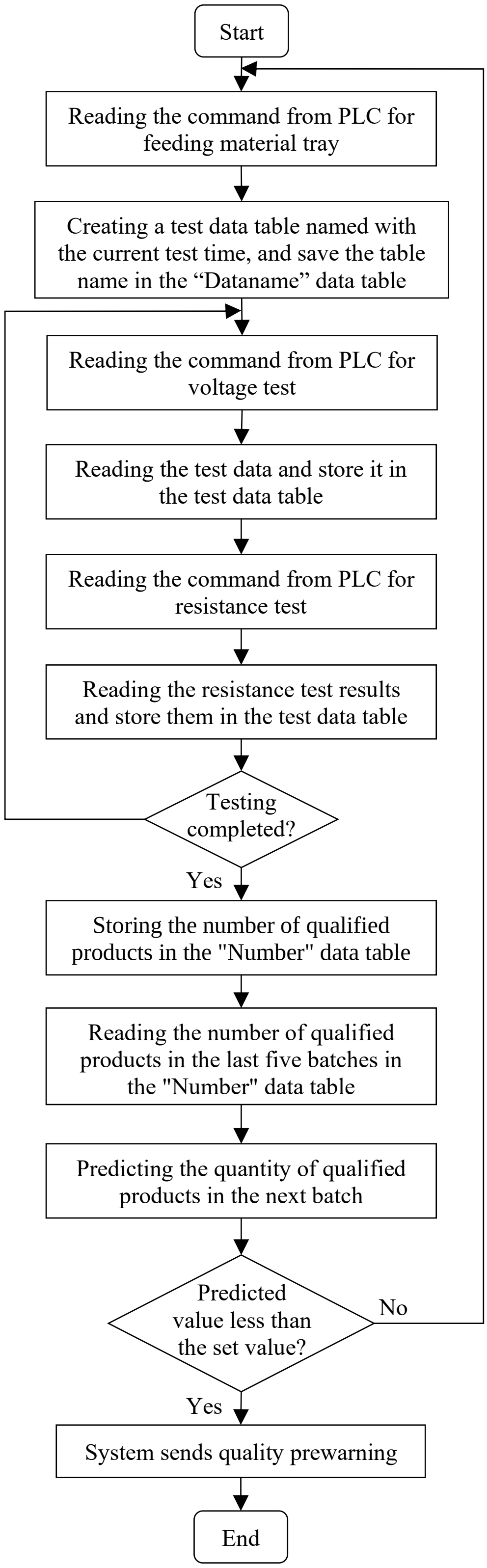

Fig. 5. Program flowchart based on LabVIEW.

For example, Fig. 6 shows the block diagram of creating a test table when the quality prewarning program reads the PLC's feeding cylinder command. Fig. 7 shows the block diagram for storing test data. After reading the test voltage command and passing a delay, the program reads the test results through NI OPC servers and stores them in the test data table. In particular, considering the emergency stop of the test platform during the test process, when reading the stop command from the PLC, query whether the test data in the test data table are sufficient for seven lines (the specification of the material tray). If there are fewer than seven lines, the program deletes the data table to avoid repeated test data. Fig. 8 shows the block diagram of quality prewarning. After the detection, the rolling modeling mechanism is used to extract the quantity of the last five batches of qualified products in the “Number” data table as the original sequence and predict the quantity of qualified products of supercapactior modules (Yao, 2003). If the predicted quantity of qualified products does not reach the set value, the system will send quality prewarning, as shown in Fig. 9.

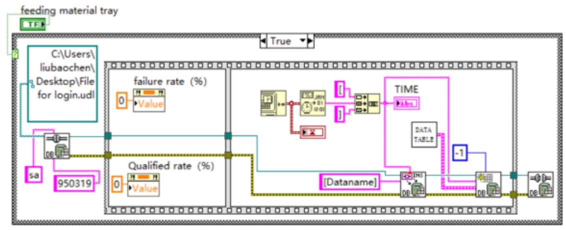

Fig. 6. Block diagram of creating the test data table.

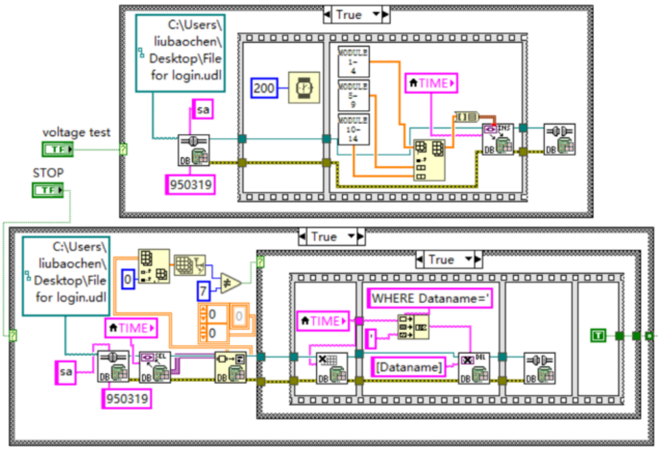

Fig. 7. Block diagram of storing test data.

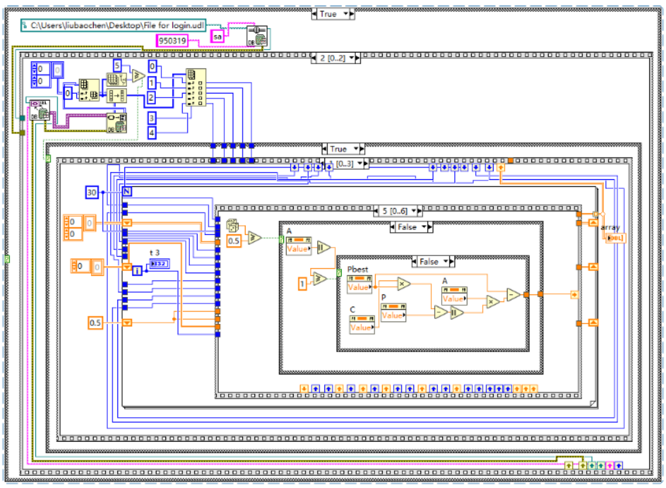

Fig. 8. Block diagram of the quality prewarning algorithm.

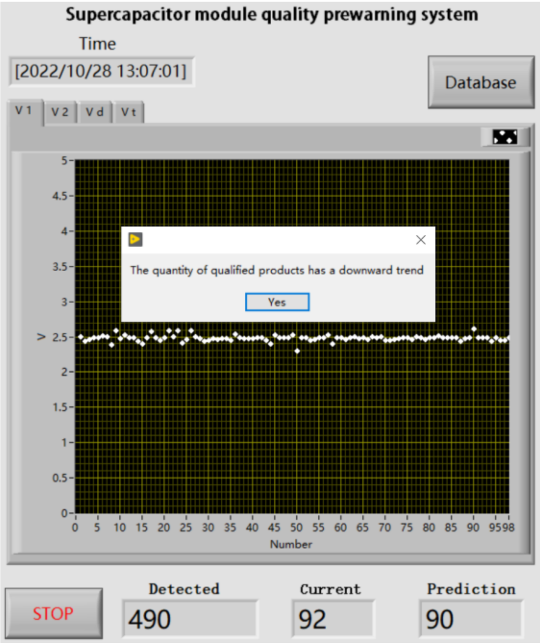

Fig. 9. System sends quality prewarning.

6. CONCLUSIONS

In this paper, an algorithm combining the improved WOA and GM (1,1) is proposed for the quality prewarning of supercapacitor modules. The main conclusions are as follows:

(1) Based on the WOA, a nonlinear iteration factor is proposed to replace the linear iteration factor of the WOA, which improves its optimization performance.

(2) The improved WOA is used to optimize the background value sequence of the GM (1,1) gray prediction model, and the superiority of the proposed algorithm combining the improved WOA and GM (1,1) in predicting the quantity of qualified products of the supercapacitor module is verified by simulation in LabVIEW software.

(3) Based on the LabVIEW software, the quality prewarning program of the supercapacitor module is compiled, and the quality prewarning function in the detection process of the test platform is realized.

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