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Grey Relational Analysis-Based Fault Prediction for Watercraft Equipment

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In this study, we aim to investigate the fault prediction for watercraft equipment by using grey relational analysis. At first, the healthy degree model of watercraft equipment is proposed, and then two main theorems are derived to determine the health condition criteria for equipment. Lastly, the relevant simulation results are provided to verify the validity and accuracy of the healthy degree model. Current results can be helpful to effectively design the supporting mode of watercraft equipment and realize the transformation of watercraft equipment support from planned maintenance to predictive maintenance.

Keywords: watercraft equipment, fault prediction, grey relational analysis, healthy degree model, predictive maintenance

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1 INTRODUCTION

Maintenance task affects the reliability and availability of equipment, which is the key factor to minimize failure time and reduce operation cost in the lifecycle of equipment [1]. Currently, the majority of methods of equipment maintenance are planned maintenance [2–10]. Among them, AKYUZ and CELIK designed an enhanced planned maintenance system (E-PMS) for a ship by using A'WOT, and their study had made a great contribution to improving the performance of equipment [2]. In practice, however, the planned maintenance is greatly influenced by the external environment and heavily depends on human effort, which leads to low efficiency and poor accuracy in the following two aspects: one is excessive maintenance, which means the unnecessary maintenance of better equipment, and the other one is insufficient maintenance, and the equipment has broken down before the maintenance period due to various reasons, but restricted by the maintenance plan, it has to operate with faults.

Therefore, fault prediction is the key to realizing the transformation of support mode from planned maintenance to predictive maintenance, which can perform the warning before the failure of equipment occurs. Also, more and more attention has been focused on fault prediction for equipment [11–22], such as fault prediction for the vehicle [11, 12], the watercraft [13–15], the aircraft engine [16–18], the power supply system [19, 20], and the track circuit [21–23]. Due to the complexity of watercraft structure and the diversity of the marine environment, it is challenging and difficult to study the fault prediction for watercraft equipment.

Over the past few years, a large number of methods were explored to predict the failure, such as the grey model [24, 25], the BP neural network [26, 27], the RBF neural network [28, 29], the data-driven model [30–33], deep learning [34], and the grey relational analysis method [35]. Although the grey models in [24, 25] were effective to a certain extent, they only considered the development of a single or several characteristic parameters independently. There were also some results that focused on theoretical research and had made some contributions [36, 37]. But their experimental data was generated from the simulation, which cannot represent the data characteristics of a real physical system. Meanwhile, a data-driven prediction method was introduced into the failure prognosis of marine diesel engines, and a discrete wavelet transform was applied to process the data based on the data characteristics [30]. In order to take multiple characteristic parameters into account comprehensively, the grey neural network model was first introduced into fault prediction for ship machinery in [38]. However, most of the existing works [30] only analyze whether the watercraft equipment will break down; they cannot explain the type of the fault and when the fault will occur. In response to the aforementioned problems, the healthy degree model based on grey relational analysis of watercraft equipment is proposed in this study, and it has been applied to a certain type of watercraft and the improvement of performance has been approved. The highlights of this study are summarized as follows.

* A novel healthy degree model is put forward by using grey relational analysis. The healthy state of watercraft equipment can be predicted by the value of the healthy degree. If the healthy degree is greater than 1, then the watercraft equipment will be healthy. If the healthy degree is less than 1, then the watercraft equipment will break down, the fault mode will be identified, and the fault occurrence time will be predicted.
* The implementation of the support mode transformation from planned maintenance to predictive maintenance can solve the three major problems: whether the watercraft equipment needs to be repaired, what kind of fault it is, and when the fault will occur.

The rest of this article is arranged as follows: at first, we describe the problem to be resolved in **Section 2**, which consists of the necessary notations and the data generation method. Then, the healthy degree model is introduced in **Section 3** to predict whether the watercraft equipment needs to be repaired, what kind of equipment fault it is, and when the fault will occur. In **Section 4**, an example of fault prediction is provided for the engine equipment in a certain type of watercraft, and the simulation results are obtained to verify the validity and accuracy of the fault prediction. Finally, some concluding remarks are made to end this study.

2 PROBLEM DESCRIPTIONS

2.1 Notations

The dataset to be tested is expressed as $X = \{x_1, x_2, \ldots, x_n\}$, where x_i $(i = 1, 2, \ldots, n)$ is an m-dimensional column vector. $y_j\,(j = 0, 1, 2, \ldots, g)$ is defined as the normalized vector which consists of the average values of every parameter in the healthy or fault state. $j = 0$ denotes that y_j is a normalized vector of healthy state. If $j \neq 0$, then y_j is a normalized vector of jth failure mode. $H_j\,(j = 1, 2, \ldots, g)$ represents the fault prediction curve of jth failure.

2.2 The Data Generation Method of Grey Relational Analysis

Since the range of watercraft equipment character parameters are different, and the values of them are not in one order of magnitude, it is very important to process the values into a comparability sequence. In fact, this processing is similar to normalization which is called data generation of grey relational analysis.

The method in [39] is used in this section since the data generation is obtained according to the attributes of character parameters.

If we wish to maximize the value of character parameter, then the value generated can be described as follows:

$$x_{ij} = \frac{y_{ij} - min\{y_{ij},\ i = 1, 2, \ldots, m\}}{max\{y_{ij},\ i = 1, 2, \ldots, m\} - min\{y_{ij},\ i = 1, 2, \ldots, m\}}\ (j = 1, 2, \ldots, n), \tag{1}$$

which is provided in [39].

If we wish to minimize the value of character parameter, then the value generated can be denoted as follows:

$$x_{ij} = \frac{max\{y_{ij},\ i = 1, 2, \ldots, m\} - y_{ij}}{max\{y_{ij},\ i = 1, 2, \ldots, m\} - min\{y_{ij},\ i = 1, 2, \ldots, m\}}\ (j = 1, 2, \ldots, n), \tag{2}$$

which is exhibited in [39].

If we wish that the value be close to the desired value y^*, then the value generated can be expressed as follows:

$$x_{ij} = 1 - \frac{\left|y_{ij} - y_j^*\right|}{max\{max\{y_{ij},\ i = 1, 2, \ldots, m\} - y_{ij}^*, y_{ij}^* - min\{y_{ij},\ i = 1, 2, \ldots, m\}\}}, \tag{3}$$

which is represented in [39].

It is obvious that the values of character parameters are transformed into the same interval $[0, 1]$. Then the healthy degree model based on grey relational analysis will be proposed in the next section.

3 HEALTHY DEGREE MODEL BASED ON GREY RELATIONAL ANALYSIS

The traditional grey relational coefficient used in [39] is calculated merely depending on the difference between two sequences. Actually, the area can represent the grey relational coefficient between two sequences; more obviously, the larger the area is, the smaller the grey relational coefficient will be. Then the area between the two sequences labeled x_i and y_j is described as follows:

$$S_{ij} = \int_0^{t_1} \left|x_i - y_j\right| dt + \int_{t_1}^{t_2} \left|x_i - y_j\right| dt + \cdots + \int_{t_{l-1}}^{t_l} \left|x_i - y_j\right| dt, \tag{4}$$

where l is the number of intersections between the two sequences, and intersections are expressed as t_k $(k = 1, 2, \ldots, l)$. The similarity whose monotonicity is opposite to the area between two sequences is structured as follows:

$$\delta_{ij} = \frac{1}{n-1}\int_2^n \frac{1}{1+\left|x_i - y_j\right|}dt. \tag{5}$$

After that, the grey relational coefficient is represented as follows:

$$r_{ij} = r\left(x_i, y_j\right) = \frac{1}{1+S_{ij}\left(1-\delta_{ij}\right)}, \tag{6}$$

where S_{ij} and δ_{ij} are the area and similarity between the two sequences, respectively. Clearly, the grey relational coefficient increases with the increase of similarity, while it decreases when the area is increased.

Finally, the healthy degree is expressed as follows:

$$h_{ij} = e^{-\left(r_{ij}-r_{i0}\right)}. \tag{7}$$

If all of h_{ij} is greater than 1 for any $i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, g\}$, then the watercraft equipment is in a healthy state. If there exists any h_{ij} smaller than 1 for $i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, g\}$, then the watercraft equipment will break down, and the failure mode can be identified as the jth failure mode.

Theorem 1. : For $\forall\ i \in \{1, 2, \ldots, n\}$, $j_k (k = 1, 2, 3) \in \{1, 2, \ldots, g\}$, if $h_{ij_1} \le h_{ij_2}$ and $h_{ij_2} \le h_{ij_3}$, then $h_{ij_1} \le h_{ij_3}$.
Proof: According to Eq. (7), the following equations can be obtained:

$$h_{ij_k} = e^{-\left(r_{ij_k}-r_{i0}\right)},\ k = 1, 2, 3. \tag{8}$$

From the known condition $h_{ij_1} \le h_{ij_2}$, we have $e^{-(r_{ij_1}-r_{i0})} \le e^{-(r_{ij_2}-r_{i0})}$. On account of which the function $f(x) = e^{-x}$ is a decreasing function, then Eq. (9) can be obtained:

$$r_{ij_1} \ge r_{ij_2}. \tag{9}$$

Based on Eq. (6), Eq. (9) can be transformed into $\frac{1}{1+S_{ij_1}(1-\delta_{ij_1})} \ge \frac{1}{1+S_{ij_2}(1-\delta_{ij_2})}$. Because the function $f(x) = \frac{1}{x}$ is a decreasing function, Eq. (10) can be acquired:

$$S_{ij_1}\left(1-\delta_{ij_1}\right) \le S_{ij_2}\left(1-\delta_{ij_2}\right). \tag{10}$$

In the same way, Eq. (11) can be deduced:

$$S_{ij_2}\left(1-\delta_{ij_2}\right) \le S_{ij_3}\left(1-\delta_{ij_3}\right). \tag{11}$$

On the basis of Eq. (10) and Eq. (11), we can obtain

$$S_{ij_1}\left(1-\delta_{ij_1}\right) \le S_{ij_3}\left(1-\delta_{ij_3}\right). \tag{12}$$

Then, we have $\frac{1}{1+S_{ij_1}(1-\delta_{ij_1})} \ge \frac{1}{1+S_{ij_3}(1-\delta_{ij_3})}$, that is,

$$r_{ij_1} \ge r_{ij_3}. \tag{13}$$

By virtue of which the function $f(x) = e^{-x}$ is a decreasing function, then Eq. (14) can be described as follows:

$$e^{-r_{ij_1}} \le e^{-r_{ij_3}}. \tag{14}$$

TABLE 1 | Normalized vector table in the states of health and three failure modes.

P	NV			
	Normal	**Fault 1**	**Fault 2**	**Fault 3**
CT/ (°C)	450.20	448.50	435.40	495.20
OP/ (*MPa*)	0.24	0.15	0.22	0.25
OT/ (°C)	58.50	45.60	72.30	75.80
FWP/ (*MPa*)	0.083	0.082	0.074	0.080
FWT/ (°C)	67.50	65.00	82.40	85.60
ET/ (°C)	426.30	430.20	419.70	500.00

Multiplying both sides of Eq. (14) by the same positive number $e^{r_{i0}}$, we have $e^{-(r_{ij_1}-r_{i0})} \le e^{-(r_{ij_3}-r_{i0})}$, that is, $h_{ij_1} \le h_{ij_3}$. Henceforth, Theorem 1 can be proved.

Theorem 2. : If $r_{ij} < r_{i0}$ for $\forall\ i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, g\}$, then the equipment will be healthy $(h_{ij} > 1)$. If there exists $r_{ij} > r_{i0}$ for $i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, g\}$, then the equipment will break down $(h_{ij} < 1)$.
Proof: Due to $r_{ij} < r_{i0}$ for $\forall\ i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, g\}$, then we can get

$$r_{ij} - r_{i0} < 0. \tag{15}$$

On account of which the function $f(x) = e^{-x}$ is a decreasing function, then Eq. (15) can be changed as follows:

$$e^{-\left(r_{ij}-r_{i0}\right)} > 1. \tag{16}$$

Based on Eq. (7), we can obtain $h_{ij} > 1$, that is, the equipment will be healthy.

With the same method, if there exists $r_{ij} > r_{i0}$ for $i \in \{1, 2, \ldots, n\}$ and $j \in \{1, 2, \ldots, g\}$, then the equipment will be judged to break down. Thus, Theorem 2 can be proved.

4 SIMULATION RESULTS

A fault prediction example is given for the engine equipment in a certain type of watercraft. Three kinds of common faults are chosen to establish the healthy degree model. Fault 1 is excessive clearance of the crankpin bearing or main bearing, fault 2 is cooling water leakage, and fault 3 is propeller overload. Parameters of cylinder temperature (labeled CT), oil pressure (labeled OP), oil temperature (labeled OT), freshwater pressure (labeled FWP), freshwater temperature (labeled FWT), and exhaust temperature (labeled ET) are selected as the character parameters. According to their values of them in the states of health and three failure modes, the average value of them in each state is considered as the normalized vector which is described in **Table 1** where P is the parameter and NV is the normalized vector.

Taking time as the horizontal axis and healthy degree as the vertical axis, three kinds of fault prediction curves are represented to analyze the trend of the curve and predict the

TABLE 2 | Historical failure record of which the time period is 100 s with the failure point included.

Fault mode	Fault occurrence time/s
Fault 1	64.23
Fault 2	58.93
Fault 3	89.96

TABLE 3 | Collected data of engine equipment from normal operation to fault 1.

T/s	P					
	CT	OP	OT	FWP	FWT	ET
10	457.28	0.22	62.51	0.089	64.37	420.43
20	459.05	0.25	63.84	0.083	65.46	425.45
30	454.10	0.27	65.39	0.088	67.82	424.10
40	455.82	0.14	48.46	0.089	68.43	440.04
50	448.69	0.20	45.87	0.085	67.693	430.54
60	453.31	0.21	42.96	0.079	64.20	439.48
70	443.95	0.12	44.30	0.082	69.95	431.71
80	444.03	0.14	44.62	0.081	64.03	413.44
90	440.44	0.16	48.76	0.081	61.50	432.52
100	455.38	0.15	43.23	0.083	65.45	430.16

TABLE 4 | Healthy degree of engine equipment from normal operation to fault 1.

T/s	HD		
	H_1	H_2	H_3
10	1.0627	1.0524	1.0847
20	1.0986	1.1010	1.1236
30	1.1515	1.1381	1.1706
40	1.0270	1.0433	1.0535
50	1.0151	1.1004	1.1181
60	1.0036	1.0311	1.0407
70	0.9944	1.0368	1.0550
80	0.9928	1.0201	1.0400
90	0.9880	1.0285	1.0465
100	0.9645	1.0498	1.0624

occurrence time of the fault included. In this case, the time period is 100 s with a failure point included. The corresponding historical failure record is exhibited in **Table 2**. If the predicted results obtained by the healthy degree model are consistent with **Table 2**, then the effectiveness of the healthy degree model can be verified.

In the process of the engine equipment from normal operation to the failure of excessive clearance of the crankpin bearing or main bearing, the time period 100 s including the failure point is studied, and the data are collected every 10 s. The collected data are shown in **Table 3**, where P and T mean the parameter and time.

The generated data aforementioned are brought into the healthy degree model to calculate the healthy degree exhibited in **Table 4**, where HD is healthy degree and T is time, and the graph of fault prediction curves is displayed in **Figure 1**.

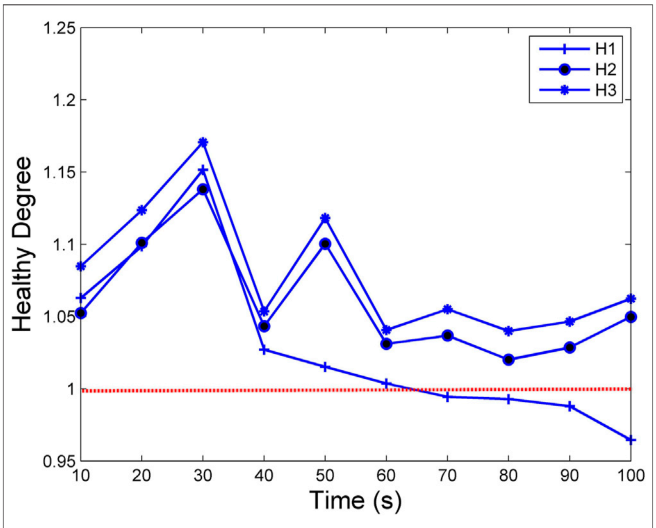

FIGURE 1 | Fault prediction curves of engine equipment from normal operation to fault 1. It is obvious that only the healthy degree of fault prediction curve of fault 1 starts to be less than 1 in the time period from 60 to 70 s, and it decreases with time.

TABLE 5 | Collected data of engine equipment from normal operation to fault 2.

T/s	P					
	CT	OP	OT	FWP	FWT	ET
10	461.44	0.22	59.92	0.091	67.74	418.83
20	465.80	0.28	55.65	0.081	67.36	437.16
30	458.57	0.25	61.26	0.084	69.93	436.04
40	452.73	0.28	61.84	0.082	70.13	412.68
50	427.16	0.22	60.08	0.092	66.05	411.70
60	435.81	0.24	71.46	0.065	68.08	428.93
70	448.64	0.29	72.35	0.072	83.40	449.87
80	468.27	0.28	72.60	0.064	84.70	421.75
90	446.62	0.30	74.84	0.052	85.60	422.67
100	432.84	0.22	82.26	0.072	88.60	423.46

TABLE 6 | Healthy degree of engine equipment from normal operation to fault 2.

T/s	HD		
	H_1	H_2	H_3
10	1.1063	1.0927	1.1222
20	1.0590	1.0661	1.0750
30	1.0580	1.0576	1.0727
40	1.0622	1.0482	1.0758
50	1.0085	1.0151	1.0458
60	1.0325	0.9945	1.0646
70	1.0134	0.9649	1.0113
80	1.0167	0.9594	1.0128
90	1.0225	0.9461	1.0170
100	1.0052	0.9325	1.0093

It is obvious that only the healthy degree of fault 1 starts to be less than 1 in the time period from 60 to 70 s, and it decreases with time. In other words, the failure of excessive

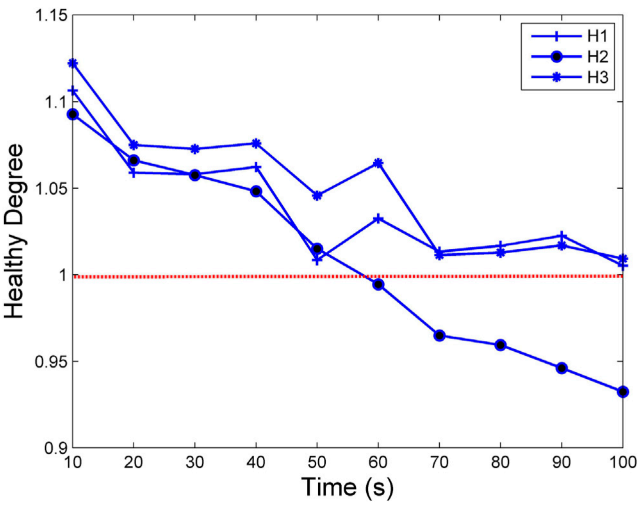

FIGURE 2 | Fault prediction curves of engine equipment from normal operation to fault 2. It is evident that only the fault prediction curve of fault 2 whose healthy degree starts to be less than 1 in the time period from 50 to 60 s.

TABLE 7 | Collected data of engine equipment from normal operation to fault 3.

T/s	P					
	CT	OP	OT	FWP	FWT	ET
10	459.49	0.27	53.55	0.088	75.40	427.18
20	453.80	0.29	64.92	0.081	67.10	446.90
30	442.14	0.30	55.29	0.087	67.13	426.98
40	445.92	0.26	53.76	0.084	65.94	421.26
50	465.42	0.25	63.57	0.083	70.44	438.60
60	465.79	0.24	60.26	0.080	70.50	452.26
70	476.66	0.22	61.60	0.083	65.51	463.03
80	467.84	0.29	62.53	0.084	69.79	474.96
90	477.45	0.22	66.69	0.088	67.64	482.24
100	466.68	0.24	59.45	0.083	74.81	496.52

TABLE 8 | Healthy degree of engine equipment from normal operation to fault 3.

T/s	HD		
	H_1	H_2	H_3
10	1.0616	1.0602	1.0798
20	1.0459	1.0455	1.0573
30	1.1771	1.1923	1.2240
40	1.0815	1.0860	1.1190
50	1.0311	1.0284	1.0391
60	1.0248	1.0243	1.0283
70	1.0098	1.0141	1.0106
80	1.0118	1.0111	1.0056
90	1.0130	1.0122	0.9989
100	1.0097	1.0084	0.9910

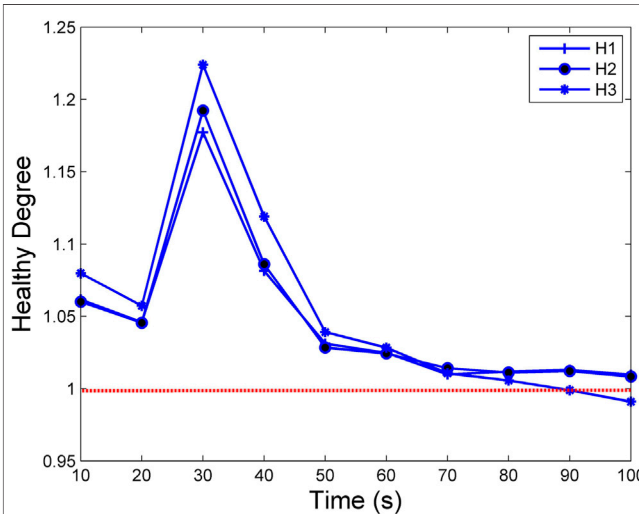

FIGURE 3 | Fault prediction curves of engine equipment from normal operation to fault 3. It is obvious that only the fault prediction curve of fault 3 whose healthy degree starts to be less than 1 when the time is close to 90 s, and the healthy degree decreases with time.

clearance of the crankpin bearing or main bearing will occur in the time period from 60 to 70 s, which is consistent with **Table 2**.

In the process of engine equipment from normal operation to fault 2, in this case, the time period is 100 s with a failure point included, and the data are collected every 10 s which is described in **Table 5**.

Based on the collected data and the healthy degree model, the healthy degree is obtained in **Table 6**, and the graph of fault prediction curves is shown in **Figure 2**.

According to **Figure 2**, only the fault prediction curve of the leakage of cooling water whose healthy degree starts to be less than 1 in the time period from 50 to 60 s, and the healthy degree decreases with time. Therefore, the fault of the leakage of cooling water will happen in the time period from 50 to 60 s, which is in line with **Table 2**.

The time period of 100 s with the failure point included is discussed in the process of engine equipment from normal operation to fault 3. The data are collected every 10 s, as shown in **Table 7**.

The collected data are used to calculate the healthy degree in **Table 8**, and the graph of fault prediction curves is displayed in **Figure 3**.

It is evident that only the fault prediction curve of the propeller overload whose healthy degree starts to be less than 1 when the time is close to 90 s, and the healthy degree decreases with time. In short, the occurrence time of the propeller overload failure will be close to 90 s, which matches the data shown in **Table 2**.

5 CONCLUSION

In summary, the healthy degree model of watercraft equipment is proposed in this article. On the basis of grey relational analysis, the healthy degree model can solve three major problems:

whether watercraft equipment needs to be repaired, what kind of fault it is, and when the fault will occur. After that, we analytically derive two theorems related to the healthy degree model, which are conducive to comprehending and applying the healthy degree model. Finally, the real data of the engine equipment in a certain type of watercraft are utilized and the relevant simulation results are provided to verify the effectiveness of the healthy degree model, and there are failure data of three types of common faults which are excessive clearance of the crankpin bearing or main bearing, the leakage of cooling water, and the propeller overload. Obviously, the predicted results of the healthy degree model are consistent with reality. The current analysis of fault prediction will be beneficial to change the support mode of watercraft equipment and realize the transformation of watercraft equipment support from planned maintenance to predictive maintenance.

In addition, there still remains a disadvantage due to the lack of failure data in this study. We will further study the generation of failure data via establishing the simulation model of watercraft equipment, carrying out the fault simulation experiment, and fully utilizing the data science in [40, 41].

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Materials, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

SF: writing the original manuscript. SF, ZC, and QG: healthy degree model analysis. SF: simulation experiment. SF and JY: revising the manuscript. CX: review, guidance, and editing. All authors have made efforts for the work and agreed to its publication.

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