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Research Article

Delphi Collaboration Strategy for Multiagent Optical Fiber Intelligent Health Monitoring System

Xiaoli Zhang [1,2] Chunfeng Fan,[3] Bianlian Zhang,[1,2] Yali Guo,[1,2] Shaofei Dong,[1,2] and Guangle Yang[1,2]

[1]*Shanxi Key Laboratory of Surface Engineering and Remanufacturing, Xi'an University, 1# Ke'ji Road, Xi'an 710065, China*
[2]*School of Mechanic & Material Engineering, Xi'an University, 1# Ke'ji Road, Xi'an 710065, China*
[3]*Henan Key Laboratory of Infrared Materials & Spectrum Measures and Applications, Henan Normal University, 46# Jian'she Road, Xinxiang 453007, China*

Correspondence should be addressed to Xiaoli Zhang; zxli_nuaa@163.com

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Optical fiber sensors are very attractive in mechanical structure intelligent health monitoring system due to some unique characteristics, such as immunity to electromagnetic interference and to aggressive environments, high sensitive and fast response, small physical dimension, excellent resolution and range, and so on. For improving the accuracy and reliability of the optical fiber intelligent health monitoring system in practical engineering application, the collaboration and decision-making strategy based on Delphi method for multiagent optical fiber intelligent health monitoring system is studied in this paper. The proposed system is mainly composed of optical fiber sensing agent, intelligent evaluation agent, and system collaborative decision-making agent. The intelligent evaluation agent is used to evaluate the health status of the monitored mechanical structures. Delphi method is used by the system collaborative decision-making agent to consult each intelligent evaluation agent. Meanwhile, the collaborative partner selection algorithm is used to select the intelligent evaluation agent participating in the collaboration, and the intelligent evaluation agent that does not participate in the decision-making is dynamically modified by the decision result. The experiment for an aircraft wing box as the typical engineering structure is carried out and the verification system is designed, the decision result is compared with that without dynamic correction of the evaluation result. The comparative results indicate that the evaluation accuracy and reliability of the monitored mechanical structural damage are improved significantly after multiple rounds of collaboration and decision making.

1. Introduction

The performance of in-service mechanical structures such as aerospace and spacecraft, bridge, and ship structures can be affected by degradation resulting from exposure to harsh flight environment conditions or damage resulting from external conditions, such as impact, loading, operator abuse, or neglect [1, 2]. In order to improve the safety level of mechanical structures, intelligent health monitoring is researched by devoting to predict the onset of damage and deterioration in mechanical structural conditions with the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors. Compared with conventional electrical sensors, optical fiber sensors have been used in intelligent health monitoring systems due to flexibility, easy fabrication and immunity to electromagnetic disturbance, and so on [3, 4]. However, so far, most of the developments on the intelligent health monitoring technology based on optical fiber sensors have been made on small size structures. For next generation mechanical structural health monitoring systems applied to large-scale structures, large-scale density sensor networks are required to be adopted to monitor different mechanical structure parameters, such as stress, strain, displacement, acoustic, pressure, and temperature [5]. Density sensors use different theories and have different functions [6]. The information each sensor gets is limited, so as its local signal processing capability. Besides, real large-scale engineering structures are very complicated systems to be estimated. Hence, to collaborate and manage the density sensor networks, to fuse the information from a number of sensors to take advantage of estimation methods to make a reliable estimation of the whole structure at an acceptable speed is still a challenge [7, 8].

Multiagent technology over the past few years has come to be perceived as a crucial technology not only for effectively exploiting the increasing availability of diverse, heterogeneous, and distributed online information sources but also as a framework for building large, complex, and robust distributed information processing systems, which exploit the efficiency of organized behavior [9, 10]. Their advantages are appropriate for application to a large-scale intelligent health monitoring system. Multiple agents collaborate, negotiate, and make decisions to achieve the solution of the problem in multiagent systems. Therefore, to apply the multiagent technology to intelligent health monitoring applications, collaboration and decision-making mechanisms are essential. Recently, a number of researchers have attempted to propose different collaboration and decision-making mechanisms. He et al. propose a novel triple-deep workflow model for production decision support problem to realize the aim of product CTQS (i.e., lower cost, faster time to market, higher quality, and better service) with manufacturing intelligence [11]. Dai et al. propose a multiagent-based computational framework for modeling decision-making and strategic interaction at the microlevel for smart vehicles in a smart world [12]. Xu et al. propose a deep reinforcement learning (RL) to deal with the cooperative decision-making problem of multiple Autonomous Underwater Vehicles (multi-AUVs) under limited perception and limited communication in attack-defense confrontation missions [13]. Somesula et al. propose Markov decision process for an efficient deep reinforcement learning algorithm [14]. Lots of researches have been made proving that the collaboration and decision-making technology is a promising one. However, the proposed theory is not universally applicable, once the application of the proposed theory is inconsistent; the collaborative decision-making strategy based on the theory is no longer applicable.

In this paper, Delphi method is proposed as a collaborative and decision-making task for multiagent optical fiber intelligent health monitoring system. The multiagent system is mainly constructed by an optical fiber sensing agent/intelligent evaluation agent/system collaborative decision-making agent. Among them, the intelligent evaluation agent can modify the health status evaluation model according to the information perceived by the optical fiber sensing agent and the feedback from the system collaborative decision-making agent. The system collaborative decision-making agent can independently plan the collaborative decision-making among the intelligent evaluation agents and dynamically modify the collaborative decision model according to the results of different intelligent evaluation agents. Thus, the collaborative decision-making work can adapt to the change of evaluation results of different intelligent evaluation agents, and the self-learning ability of the multiagent optical fiber intelligent health monitoring system is enhanced. More exactly, experimentally on the damage loading position prediction of an aircraft wing box with four optical fiber sensing agents, four intelligent evaluation agents, and one system collaborative decision-making agent, the performance of the proposed method is verified. As a result, the proposed technique can improve the accuracy and reliability of the whole optical fiber intelligent health monitoring system.

2. Multiagent Collaboration and Decision-Making Strategy Based on Delphi Method

2.1. Delphi Method. Expert-opinion is gathered using the Delphi method. This involves a structured consultation with a panel of specialists about a particular problem, typically involving several rounds, in which experts express their views and consider each other's opinions before making a final judgment. The method has been used for forecasting future developments [15, 16]. Here, each intelligent evaluation agent is taken as an expert system; the collaborative decision-making agent modifies its decision results through more rounds consultation, feedback, and analysis. In each round, the result is fed back to the intelligent evaluation agent, together it modifies its damage evaluation result and relies on the decision conclusion, again feedback to the system collaborative decision-making agent. Thus, a more accurate and more reliable result is formulated based on a number of different specialists.

2.2. Delphi Method for Collaboration and Decision-Making Strategy. The schematic diagram of the collaboration and decision-making strategy based on Delphi method is shown in Figure 1. The working process is described as follows. The evaluation results about the health status of the monitored mechanical structure are transmitted to the system collaborative decision-making agent by each intelligent evaluation agent, and the optimal evaluation results are selected to participate in the collaboration. The selection method for a participant in the collaboration can refer to reference [17]. In this process, the mean square error value of the intelligent evaluation result of the agent is determined as the weight of each expert, and the weight is determined as follows. If the mean square error of each intelligent evaluation agent during training is $x_1, x_2, \ldots, x_N$ separately, then the weight of expert 1 is $p_1 = x_1/(x_1 + x_2 + \cdots x_N)$, the weight of expert 2 is $p_2 = x_2/(x_1 + x_2 + \cdots x_N)$, and the weight of expert is $p_N = x_N/(x_1 + x_2 + \cdots x_N)$.

System collaborative decision-making agent makes their decision; the decision method is as follows: (1) weighted average is carried out by the participant intelligent evaluation agents, so the final decision is obtained, and the decision result is taken as the round 1 evaluation result. (2) For the intelligent evaluation agents that do not participate in round 1, its evaluation model is modified dynamically by taking the round 1 decision results as the new samples. Simultaneously, the corrected intelligent evaluation model reevaluates the health status of the monitored mechanical structure; again the evaluation result is transmitted to the system collaborative decision-making agent. (3) Relying on the collaborative partner selection algorithm, the system collaborative decision-

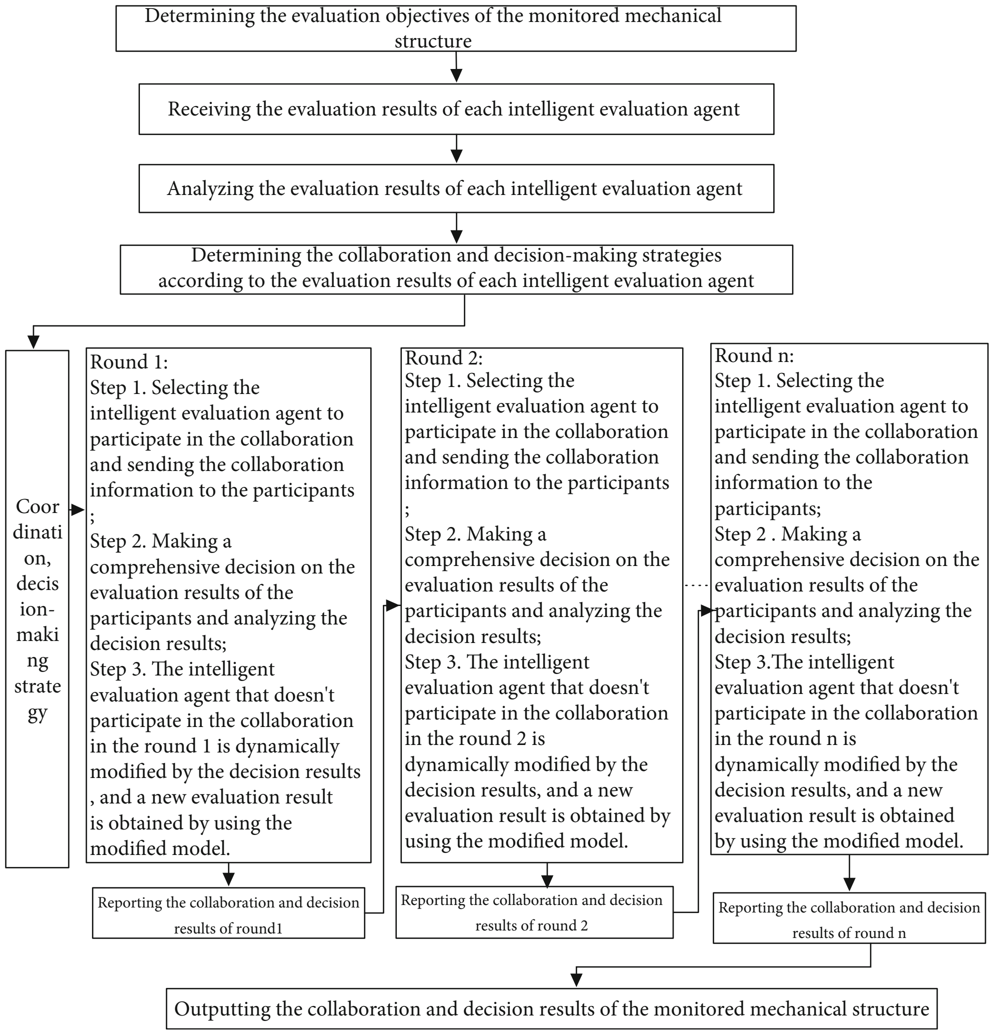

Figure 1: Collaboration and decision-making strategy based on Delphi method.

making agents select the participant intelligent evaluation agents again, and their weights are redetermined again, thus the round 2 decision result is obtained again. After more rounds, each health status evaluation result is monitored, mechanical structure in each agent arrives at the optimum, and the collaboration process is over. Furthermore, if the intelligent evaluation agent selected by the partner selection algorithm no longer changes, the collaborative decision-making process is also terminated, and the last round decision result is used as the final evaluation result of the health status of the monitored mechanical structure. During the whole of this session, the intelligent evaluation model and collaborative decision model can be modified dynamically, thus the collaboration and decision performance is improved.

3. Experimental Investigation

3.1. Optical Fiber Sensing Principle. Fiber Bragg grating (FBG) sensor is an important branch of optical fiber sensor, and it has a wide application prospect in mechanical structure health monitoring. A fiber Bragg grating (FBG) is a type of distributed Bragg reflector installed in a short optical fiber segment that reflects particular light wavelengths and transmits all others. This is achieved by generating a periodic change in the fiber core refractive index, which produces a dielectric mirror unique to the wavelength [18]. Generally, fiber Bragg gratings are created using an extreme ultraviolet (UV) source such as a UV laser by systematical variation of the refractive index at the center of a special type of optical fiber [19]. Fresnel reflection is the fundamental principle behind the operation of an FBG, where light moving through media with different refractive indices at the interface will reflect and refract. The reflected wavelength is known as the Bragg central wavelength (λ_B): $\lambda_B = 2n_{\text{eff}}\Lambda$, where n_{eff} is the effective refractive index of the grating in the fiber core and Λ is the grating period [20, 21]. Just as the equation shows, the shift of the Bragg central wavelength λ_B can be determined by the change of n_{eff} and Λ, which relates to strain and temperature [22]. If the temperature keeps invariability, certain loads are applied on the monitored mechanical structure, and the strain distribution on the mechanical structure can be monitored by the Bragg

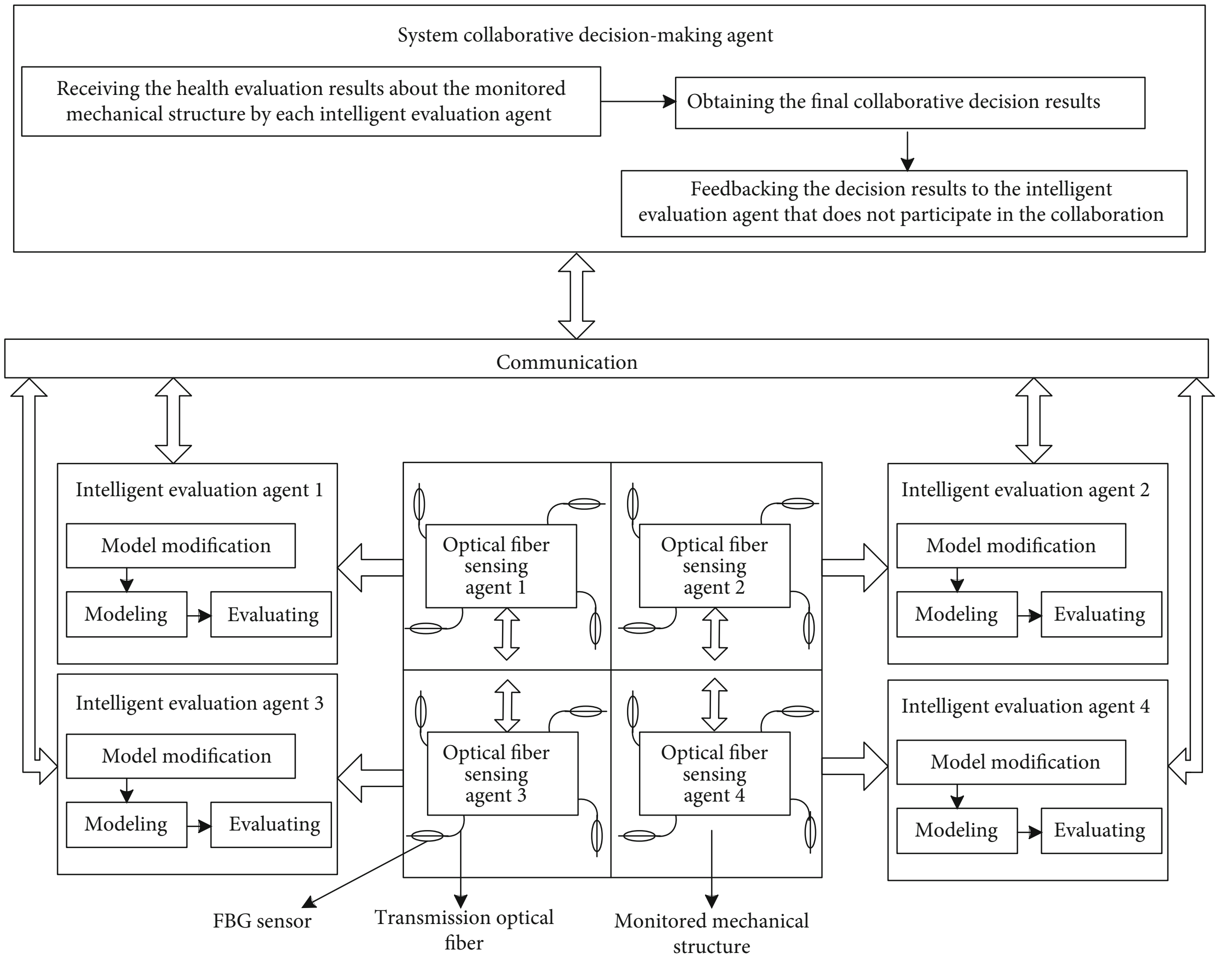

Figure 2: Schematic diagram of multiagent optical fiber system.

central wavelength shift. Based on the mentioned principle, mechanical structural damage can be monitored with the FBG sensors, which are glued to or embedded in the mechanical structure.

3.2. Experimental System Setup. Intelligent health monitoring system has currently become the highlight of researches and applications in mechanical structure engineering. And its core is damage detection and identification. As is known, it is a challenge to perform accurate damage analysis, especially the damage position via global information [23]. Therefore, to validate the efficiency of the multiagent optical fiber intelligent health monitoring system, an aircraft wing box as the typical engineering structure to monitor the local damage load is adopted. The aircraft wing box is composed of aluminum alloy and carbon fiber, and it is divided into 7 rows and 6 columns, altogether 42 cells by fiber reinforcement and screen, and four sides of the aircraft wing box are fixed by the screw and frame. In this study, four neighboring cells are chosen to carry out the experiment, and 21 FBG sensors are arranged in the experimental area. To separate the temperature effect from the strain, a not bonded FBG sensor is used as a reference so that the temperature effect can be subtracted from the FBGS bonded in the aircraft wing box. With this procedure, the measurement of the real strain on the sample is assured. The schematic diagram of the multiagent system is shown in Figure 2. 21 FBG sensors are reasonably divided into four optical fiber sensing agents. Correspondingly, there are four intelligent evaluation agents and one system collaborative decision-making agent. When a load is applied to the aircraft wing box, FBG sensors with the optical fiber sensing agent will obtain the strain information about the monitored mechanical

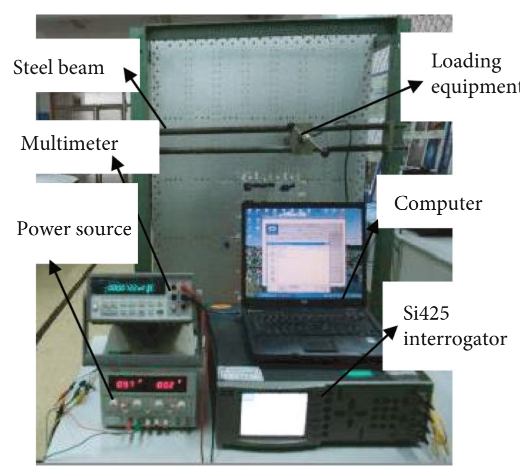

Figure 3: Experimental system.

Table 1: Results of each intelligent evaluation agent and system collaborative decision-making agent for (826, 375).

Agent number		Agent 1	Agent 2	Agent 3	Agent 4	Decision result	Error
Round 0	Result	(831.4, 378.3)	(905.9, 369.5)	(853.5, 382.2)	(832.5, 400.7)	(856.6, 383.2)	31.7
	Weight	(0.21, 0.26)	(0.24, 0.23)	(0.32, 0.24)	(0.23, 0.27)		
Round 1	Result	(831.4, 378.3)	⋇	(853.5, 382.2)	(832.5, 400.7)	(841.1, 387.4)	19.5
	Weight	(0.275, 0.333)	(0, 0)	(0.418, 0.316)	(0.307, 0.351)		
Round 2	Result	(831.4, 378.3)	(858.4, 378.6)	(853.5, 382.2)	⋇	(846.4, 379.5)	20.9
	Weight	(0.27, 0.29)	(0.31, 0.44)	(0.41, 0.27)	(0, 0)		
Round 3	Result	⋇	(858.4, 378.6)	(853.5, 382.2)	(813, 378.3)	(841.3, 379.9)	16.1
	Weight	(0, 0)	(0.31, 0.28)	(0.35, 0.42)	(0.34, 0.3)		

Table 2: Results of each intelligent evaluation agent and system collaborative decision-making agent for (934, 407.5).

Agent number		Agent 1	Agent 2	Agent 3	Agent 4	Decision result	Error
Round 0	Result	(979.4, 381.2)	(945.9, 398.7)	(928.6, 404.6)	(919.4, 458.5)	(941.3, 410.9)	8
	Weight	(0.21, 0.26)	(0.24, 0.23)	(0.32, 0.24)	(0.23, 0.27)		
Round 1	Result	(979.4, 381.2)	(945.9, 398.7)	(928.6, 404.6)	⋇	(947.7, 394.5)	18.9
	Weight	(0.27, 0.35)	(0.31, 0.32)	(0.42, 0.33)	(0, 0)		
Round 2	Result	⋇	(945.9, 398.7)	(928.6, 404.6)	(921, 419.2)	(931.3, 407.8)	2.7
	Weight	(0, 0)	(0.303, 0.313)	(0.4, 0.325)	(0.296, 0.36)		

structure. Thus, strain data that indicate mechanical structural damage are obtained. The mechanical structural strain data collected by the FBG sensors are processed in the optical fiber sensing agent. Then, they are transmitted to the corresponding intelligent evaluation agent, and the mechanical structural damage is evaluated by the evaluation model. In each intelligent evaluation agent, the support vector regression machine (SVRM) algorithm is adopted to evaluate the structural damage; the evaluation algorithm can refer to previous research [24, 25]. This way, the evaluation results and the weight about the health status of the monitored mechanical structure in each intelligent evaluation agent are transmitted to the system collaborative decision-making agent, and the optimal evaluation results are selected to participate in the collaboration. Weighted average is carried out by the participant intelligent evaluation agents, so the final decision is obtained and sending the collaboration and decision results to each intelligent evaluation agent. Relying on the decision results from the system collaborative decision-making agent, the intelligent evaluation agent that does not participate in the collaboration will dynamically modify its evaluation model and evaluation result. Meanwhile, the system collaborative decision-making agent receives the evaluation results again and dynamically modifies the collaborative decision model and decision results, until the optimal evaluation results are achieved.

The experimental system is shown in Figure 3. The loading equipment is fixed on the steel beam, and it can move along the beam freely, meanwhile, the steel beam can move up and down freely. With this, any damage loading position of the aircraft wing box can be applied in the length and width direction. In the selected experimental area, ninety-nine damage loading points are selected and the magnitude of the damage loading is 140 N, 175 N, and 210 N separately at each loading point. When the damage loading is applied to the aircraft wing box, the Bragg central wavelength of the FBG sensors embedded in the aircraft wing box will shift, and the shift is demodulated by Si425 interrogator and the data are stored in the computer. Simultaneously, the magnitude of the damage load is obtained by the conversion of the voltage values displayed in the multimeter. This way, the data information including the position and Bragg central wavelength shift at each damage loading position are achieved in the optical fiber sensing agent.

3.3. Experimental Results and Discussion. In the experimental area, 4 damage locations are randomly selected from each optical fiber sensing agent, and the specific location of the selected damage is (826, 375), (934, 407.5), (880, 505), and (1042, 472.5), separately. The evaluation result of each intelligent evaluation agent and decision-making results of the system collaborative decision-making agent in the four damage locations are graphically demonstrated in Tables 1–4. As seen from the tables, for the damage locations (826, 375), (934, 407.5), (880, 505), and (1042, 472.5), the final decision result representing the distance error between the actual value and decision value is 16.1, 2.7, 5.9, and 2.7, separately. Compared with the previous decision result that the evaluation model and evaluation result of the intelligent evaluation agent and the collaborative decision model and the decision results of the collaborative decision-making agent are not modified dynamically, the distance error of most monitored damage locations decrease, that is, the evaluation accuracy of the damage locations becomes higher, the previous decision results can refer to previous research [26]. For the damage

Table 3: Results of each intelligent evaluation agent and system collaborative decision-making agent for (880, 505).

Agent number		Agent 1	Agent 2	Agent 3	Agent 4	Decision result	Error
Round 0	Result	(874.6, 508.3)	(879.5, 507.9)	(879.5, 495.6)	(864.3, 496.6)	(874.9, 501.9)	5.9
	Weight	(0.21, 0.26)	(0.24, 0.23)	(0.32, 0.24)	(0.23, 0.27)		

Table 4: Results of each intelligent evaluation agent and system collaborative decision-making agent for (1042, 472.5).

Agent number		Agent 1	Agent 2	Agent 3	Agent 4	Decision result	Error
Round 0	Result	(1037.1, 475.8)	(1080.3, 483.6)	(1110.6, 475.8)	(1032.3, 466.7)	(1069.9, 475.1)	28
	Weight	(0.21, 0.26)	(0.24, 0.23)	(0.32, 0.24)	(0.23, 0.27)		
Round 1	Result	(1037.1, 475.8)	(1051.2, 482.6)	※	(1032.3, 466.7)	(1040.4, 474.7)	2.7
	Weight	(0.31, 0.34)	(0.35, 0.31)	(0, 0)	(0.34, 0.35)		

locations (826, 375), (934, 407.5), and (1042, 472.5), the collaborative decision-making agent selects the collaborative partner and makes several rounds of dynamic correction to the intelligent evaluation agent that does not participate in the collaboration, compared with the decision result without selecting the collaborative agent, the decision result represents the distance error between actual value and decision value is decreased by 49.2%, 66.3%, and 90.4%, respectively, the decision accuracy becomes higher and higher after multiple rounds of collaborative decision making. For the damage location (880, 505), relying on the participant selection strategy, four intelligent evaluation agents are selected to participate in the collaboration, the distance error between the actual value and decision value is only 5.9 mm, the decision accuracy is higher, and the collaborative partner no longer changes.

(Remark: Round 0 denotes the unselecting collaborative agent, namely, all intelligent evaluation agents participate in the collaboration. ※ denotes the intelligent evaluation agent that does not participate in the collaborative decision-making process. Agent 1, Agent 2, Agent 3, and Agent 4 denote each intelligent evaluation agent. Error denotes the distance error between the actual value and decision value, unit is mm)

4. Conclusions

In practical applications of intelligent health monitoring system, a large number of distributed sensors are usually adopted to monitor large-scale mechanical structures and different kinds of damage. The monitored mechanical structures are usually divided into different substructures and monitored by a large number of sensors. Under this situation, how to manage the distributed sensors and deal with the distributed information obtained by these sensors at different sites on the structure, meanwhile, obtaining an accurate evaluation result is an important problem. In this paper, multiagent optical fiber intelligent health monitoring system based on Delphi collaboration strategy is researched in detail. An architectural model of an intelligent health monitoring system with multilayer and multiagent structures distributed is proposed. In the proposed architectural model, the decision result based on Delphi is used to dynamically modify the evaluation model of noncooperative intelligent evaluation agent. Simultaneously, the health status of the monitored structure is reevaluated by the corrected intelligent evaluation model, and the evaluation result is transmitted to the system collaborative decision-making agent again. During the process, the intelligent evaluation model and collaborative decision model can be both modified dynamically. For the randomly selected damage locations in the experiment, the final decision result representing the distance error between the actual value and the decision value is at least decreased by 49.2%. Therefore, the evaluation accuracy of the monitored damage structure is improved significantly after multiple rounds of collaboration and decision making. These studies successfully demonstrate that the proposed collaboration and decision-making strategy based on Delphi can achieve the interaction and collaboration among different agents, thus the evaluation accuracy and reliability of optical fiber intelligent health monitoring system are improved. The research results will not only provide theoretical and practical reserves for the optical fiber intelligent health monitoring system but also promote the practical application of the optical fiber intelligent health monitoring system. For the limitation of this paper, although four damage points were analyzed in the experiment, for the other damage points, it is not to, and can be achieved by this method. This study result is not only useful for high reliability and accuracy intelligent health monitoring system but also if partial optical fiber sensors are invalid, it can provide reference for the self-repairing ability of the intelligent health monitoring system in the engineering application.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no financial and personal relationships with other people or organizations that could have appeared to influence the work reported and publication in this paper.

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