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Displacement Values Calculation Method for Ship Multi-Support Shafting Based on Transfer Learning

Yibin Deng [1,*], Yuefan Li [2], Hanhua Zhu [1] and Shidong Fan [2]

1 School of Naval Architecture, Ocean and Energy Power Engineering, Wuhan University of Technology, Wuhan 430063, China; hh.zhu@163.com
2 School of Transportation and Logistics Engineering, Wuhan University of Technology, Wuhan 430063, China; liyuefan@whut.edu.cn (Y.L.); sdfan@whut.edu.cn (S.F.)
* Correspondence: dengyb@whut.edu.cn

Abstract: Deviations between the design and actual shafting occur due to limitations in ship construction accuracy. Consequently, accurately obtaining the relationship between the actual shafting load and displacement relationship based on the design shafting becomes challenging, leading to inaccurate solutions for bearing displacement values and low alignment efficiency. In this research article, to address the issue of incomplete actual shafting data, a transfer learning-based method is proposed for accurate calculation of bearing displacement values. By combining simulated data from the design shafting with measured data generated during the adjustment process of the actual shafting, higher accuracy can be achieved in calculating bearing displacement values. This research utilizes a certain shafting as an example to carry out the application of the bearing displacement value calculation method. The results show that even under the action of shafting deviation, the actual shafting load and displacement relationship model can become more and more accurate with the shafting adjustment process, and the accuracy of bearing displacement values calculation becomes higher and higher. This method contributes to obtaining precise shafting adjustment schemes, thereby enhancing alignment quality and efficiency of ship shafting.

Keywords: multi-support shafting; shafting alignment; transfer learning; bearing displacement value calculation

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1. Introduction

The alignment quality of the propulsion shafting is a critical factor influencing ship propulsion performance [1]. High-quality alignment of shafting is an important guarantee for safe navigation [2,3]. Poor alignment quality can result in excessive bearing force, abnormal wear, or even shafting failure, leading to power loss and hindered sailing capability [4–7]. For example, elementary mistakes have been discovered in the shaft alignment of the HMS Prince of Wales: both the GBP 3 billion warship's starboard and portside shafts are misaligned, causing the shafts to be offset. This situation has seriously affected its normal navigation [8]. The alignment quality of the propulsion shafting relies on meticulous design and installation processes. Therefore, strict specifications must be followed during the inspection of its design, manufacturing, and installation procedures to ensure alignment quality [9,10].

Shafting alignment involves precise installation according to design shafting specifications—a meticulous process within shipbuilding procedures. The bearing height adjustments typically require accuracy to 0.01 mm. When a ship under construction moves from the shipyard to the wharf, the hull is deformed due to the change of support forms and ambient temperature. In addition, the main engine hoisting will also cause local deformation of the hull and the shaft line will be deformed accordingly. Therefore, the shafting alignment and adjustment work is usually arranged after the ship is launched and the main engine is hoisted. However, this causes another problem: since it becomes difficult to establish a precise bearing height reference standard after launching the ship, evaluating the installation quality solely based on direct measurement of bearing height is not feasible. Consequently, the shafting alignment quality is inspected directly by measuring the bearing load.

Shafting alignment is conducted through an iterative process involving bearing load checking, bearing displacement values calculation, and implementation of bearing displacements until all the bearing loads pass the check. Bearing load checking entails measuring the bearing load to determine if it falls within the allowable deviation range. If not, a scheme for adjusting the shaft needs to be developed by calculating and implementing appropriate displacement values for the bearings. Among them, calculating accurate bearing displacement values is crucial in achieving proper shafting alignment, as it reduces adjustment times and improves efficiency.

Currently, the trial-and-error method is commonly employed to determine bearing displacement values by repeatedly comparing deviation direction and magnitude between measured loads and design loads until they converge towards each other. This method works well for short shafts with a single support where only one variable needs to be adjusted iteratively. However, for a multi-support long shaft system with the engine room arranged in the front or middle of the hull, it becomes a multivariate solution problem with increased constraints that limit effective adjustment of bearings. Additionally, there exists a mutual coupling relationship between bearing loads which makes it challenging to find combinations of height adjustments that satisfy all specifications solely through the trial-and-error method. Therefore, achieving efficient shafting alignment primarily relies on experienced technicians.

To overcome the limitations of the trial-and-error method, a more scientific and rational approach involves utilizing the design shafting bearing load and displacement relationship as a basis for determining the bearing displacement values. This approach considers the interdependent relationship between bearing loads and employs numerical calculations using methods such as the three moment method [11,12], transfer matrix method [13], singular function method [14], or finite element method [15] to obtain the influence number matrix representing changes in bearing load caused by unit changes in bearing height. Based on this, the minimum bearing load of the stern tube [16] or the minimum adjustment displacement [17] is taken as the optimization objective function, the allowable deviation and rotation angle of the bearing load are taken as the constraint conditions, and optimization algorithms such as linear programming [18] and quadratic programming [19] are employed to calculate the bearing displacement values. In order to reduce the computational complexity of the shafting alignment caused by the optimization algorithm, Deng et al. [20] take the simulated data of the design shafting numerical model as a training sample to represent the relationship between bearing load and height. It then becomes possible to input measured loads from the current shafting state with designed loads into this neural network model during shafting alignment site operations, thereby obtaining current heights and design heights for each bearing which can then be compared to derive their corresponding displacement values. It is worth noting that the aforementioned method is based on the design shafting model, while the actual shafting during alignment is formed through processing, manufacturing, and installation processes as depicted in Figure 1. However, deviations exist between them due to manufacturing errors, positioning errors, and assembly errors [21,22], leading to incomplete agreement between the actual and design shafting bearing load and displacement relationship. Therefore, the effectiveness of this method for alignment depends on the magnitude of these deviations. Given the current limitations in shipbuilding accuracy, further improvements are required to enhance its practical applicability.

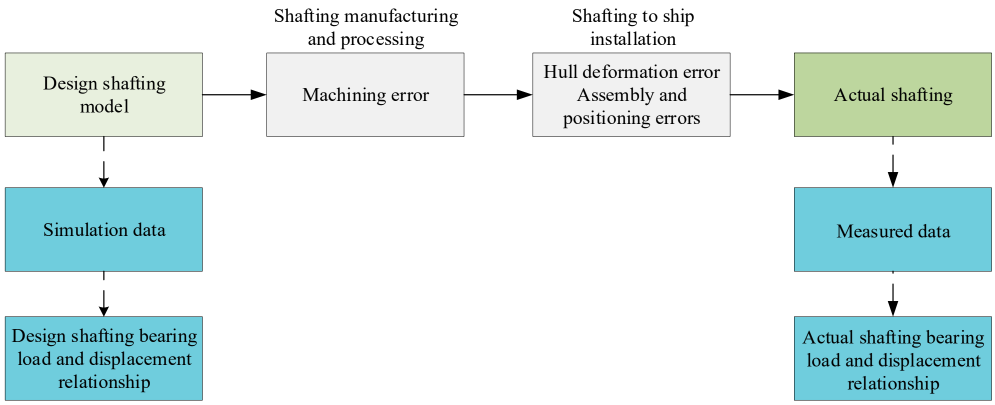

Figure 1. Design shafting to actual shafting evolution.

Due to the limitations in shipbuilding accuracy and the complex coupling characteristics between shafting bearing loads, multi-support shafting alignment becomes a more challenging task. The personnel responsible for shafting assembly often encounter numerous repeated adjustment attempts, which can lead to difficulties in identifying the adjustment rules, loss of direction, and even greater deviations in bearing loads with each subsequent adjustment. Consequently, this results in prolonged alignment periods for the shafting and low efficiency in adjustments. For instance, one study [23] mentioned a delay of more than 4 months in dock assembly after ship launching, with a shafting adjustment period lasting as long as 31.5 weeks. Another study [24] mentioned that the intermediate shafting adjustment of a ship took as long as 35 days, accounting for 72% of the total shafting installation period and significantly impeding ship construction progress.

Building upon previous study [20], Deng et al. considered the deviation between the design shafting and the actual shafting, respectively using the model simulation data representing the design shafting and the measured data generated in the shafting alignment process to represent the actual shafting, and trained the neural network model with different confidence levels, so as to improve the accuracy of determining bearing displacement values [25]. However, since the bearing height datum cannot be found after the ship is launched, the bearing height defined by this method is not easy to obtain in engineering applications.

The key factor for accurately calculating bearing displacement values lies in establishing an accurate actual shafting load and displacement relationship. This relationship evolves from the design shafting, undergoing various error condition. The design shafting is completely known, and the measured data of the actual shafting can be obtained gradually during the alignment process. Therefore, establishing the relationship between the actual shafting bearing load and displacement relationship becomes a modeling problem under incomplete information conditions. It is essential to construct the actual shafting bearing load and displacement relationship model based on the design shafting model and limited measured data.

Transfer learning, as an emerging machine learning algorithm, has been widely employed to address incomplete information problems by overcoming isolated learning methods [26]. By transferring relevant knowledge from known models, transfer learning reduces the reliance of target models on extensive target data and enables construction with only a small amount of target data available. Shahin et al. [27] utilized a transfer learning method based on regularization to eliminate the negative impact caused by missing information in incomplete target domain datasets and developed a prediction model suitable for the target domain. Zheng et al. [28] applied fuzzy sets for data processing and conducted co-evolutionary transfer learning using different types of training data to overcome limited training samples when constructing practical models. Xiao et al. [29] considering transfer learning as their primary solution, reduced weightage assigned to negative samples through loss functions to tackle the problem of inaccurate and incomplete vehicle trajectory collection data, and constructing a trajectory prediction framework aligned with actual environments.

This research article proposes a calculation method for determining the bearing displacement values of multi-support shafting based on transfer learning. By utilizing the transfer learning method, the actual shafting bearing load and displacement relationship model is constructed using both the design shafting model and measured data from the adjustment process. Then, bearing displacement values are further obtained. This research mainly comprised (1) establishing a neural network model to characterize the functional relationship between the load values before displacement, the load values after displacement, and displacement values of the intermediate bearing, and (2) utilizing the transfer learning approach, deriving the actual shafting bearing load and displacement relationship based on the design shafting model and measured data from adjustment process. As more measured data accumulates during the adjustment process, this model progressively improved in accuracy. (3) Considering the mounting positioning deviation of the stern bearing and main engine in different degrees, the application effect of this method was evaluated by the simulated process of adjusting a particular ship's shafting.

2. Calculation Method of Bearing Displacement Values Based on Transfer Learning

2.1. General Idea of Calculating the Bearing Displacement Value

The overall concept is illustrated in Figure 2. The left side of the figure depicts the elements associated with design shafting, including the establishment of a numerical model based on design parameters and the utilization of simulation data to derive a bearing load and displacement relationship model for the design shafting. On the right side, elements related to actual shafting are presented, primarily encompassing installation and adjustment processes. Two main connections exist between the designed and actual shafting: firstly, the design shafting is subject to various error factors that contribute to the formation of the actual shafting; secondly, by leveraging the shafting bearing load and displacement relationship of the designed shafting, transfer learning is combined with measured data from the actual shafting to establish the bearing load and displacement relationship for the actual shafting. This model is then used to acquire bearing displacement values and implement bearing displacement, conduct load and displacement tests, and verify bearing loads. In the iterative process of shafting alignment, the number of cycles is also the number of shafting adjustments. Transfer learning can be performed during each cycle, so the accuracy of the neural network model characterizing the actual bearing load and displacement relationship will improve with the increase of adjustment times. Consequently, more accurate bearing displacement values are obtained. Finally, evaluating the effectiveness of calculating bearing displacement values relies on the number of adjustments and assessing errors between measured loads and design loads.

2.2. Modeling the Design Shafting Bearing Load and Displacement Relationship

A study [20] constructed a neural network model of design shafting bearing load and height relationship, as depicted in Figure 3. However, measuring the bearing height in engineering is challenging and its practical application is difficult. In this research, the transfer learning method approach was applied by considering the design shafting bearing load and displacement relationship model as the fundamental model and combining it with the measured data from the actual shafting alignment process. For a shafting with 'n' intermediate bearings, Figure 4 illustrates the neural network topology constructed. The input of the model consists of each intermediate bearing load value before and after displacement, while the output represents the corresponding displacement values. The number of intermediate hidden layers was set to 2. The training sample of the model was calculated using the design shafting numerical model, which also held the necessary data for the actual shafting alignment process.

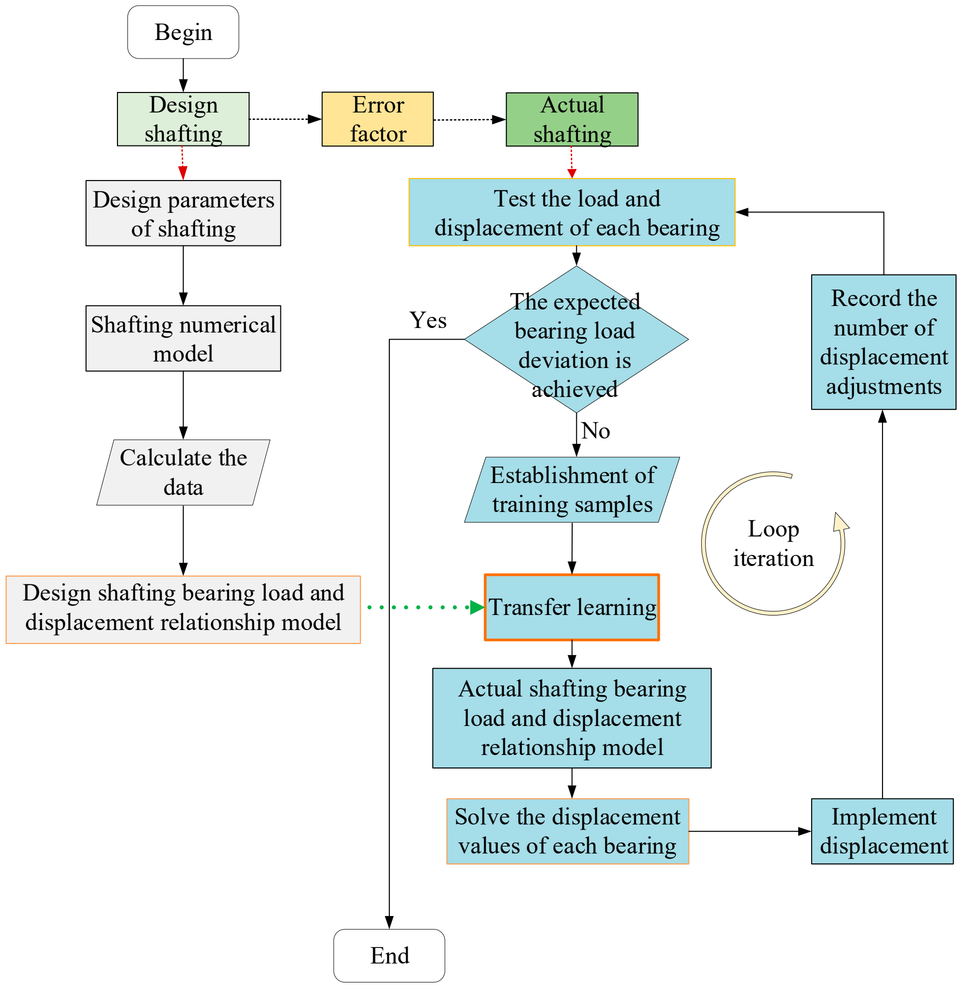

Figure 2. Flowchart of the method.

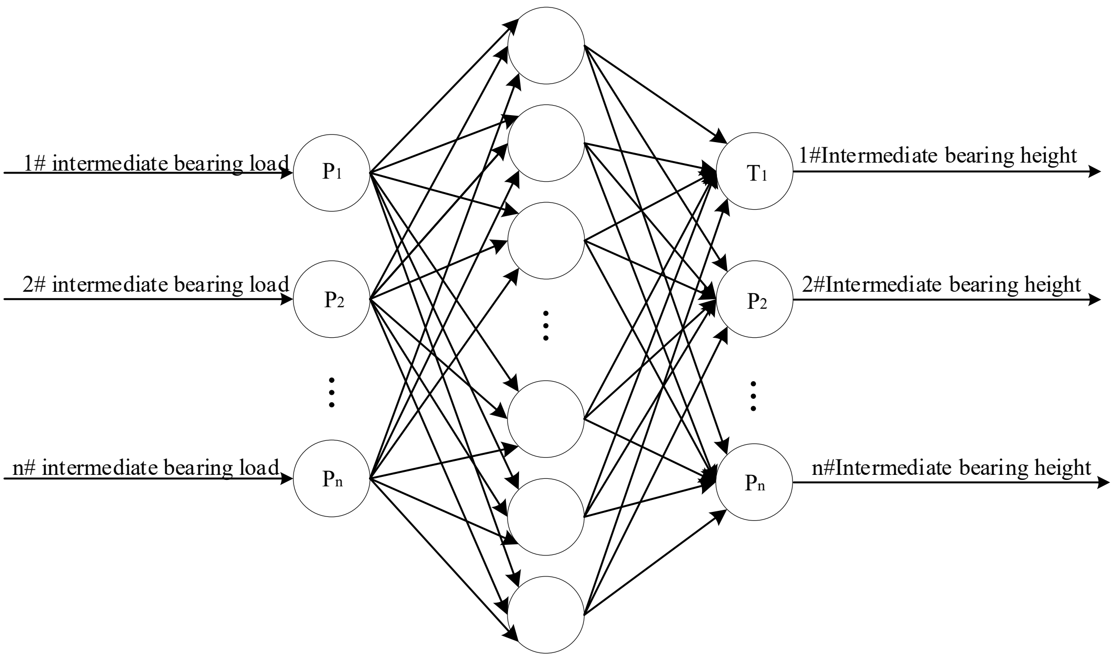

Figure 3. Neural network topology based on bearing load and bearing height.

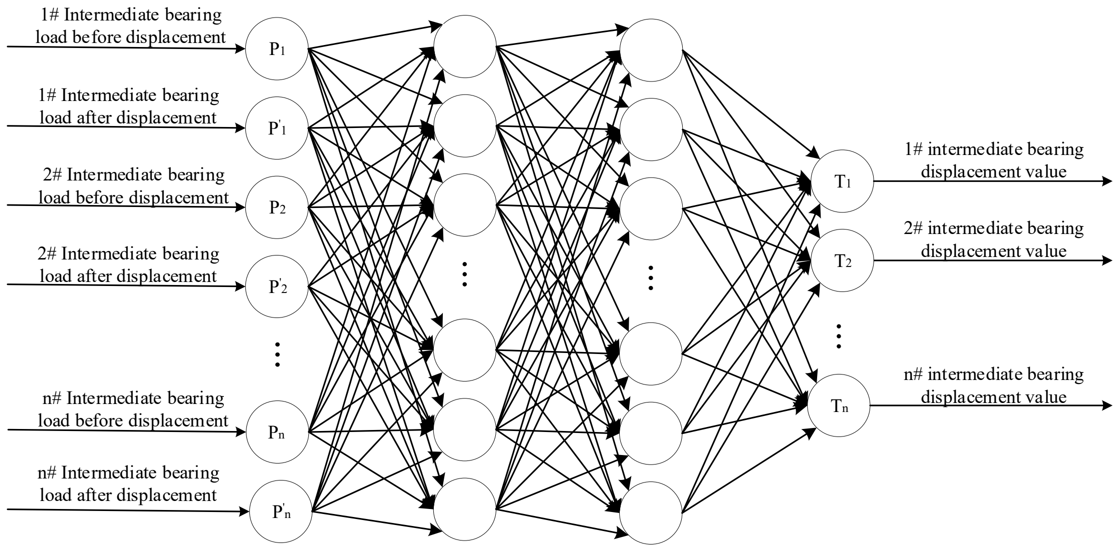

Figure 4. Neural network topology based on bearing load and bearing displacement.

2.3. The Measurement of Shafting Alignment Parameters and the Construction of Training Samples

Displacement sensors were placed on each intermediate bearing to accurately measure their displacements, while the dynamometer method, jacking method or strain gauge method were employed to measure loads on these bearings. During the shafting adjustment process, initial loads on all bearings [$f_1$1, $f_2$1, ..., f_n1] were initially measured before any displacements were implemented. Subsequently, adjustments were made based on calculated displacement values, followed by measurements of individual bearing displacements [$d_1$1, $d_2$1, ..., d_n1], and loads after displacement adjustments [$f_1$2, $f_2$2, ..., f_n2]. The loads before and after displacement for each bearing, along with their corresponding displacement values obtained during the adjustment process, constituted a set of measured samples representing the actual shafting [$f_1$1, $f_2$1, ..., f_n1; $f_1$2, $f_2$2, ..., f_n2; $d_1$1, $d_2$1, ..., d_n1].

Accumulating a larger volume of measured samples enhances the effectiveness of transfer learning. Existing measured data can be combined to expand the sample set. For instance, considering two adjacent sample groups [$f_1$1, $f_2$1, ..., f_n1; $f_1$2, $f_2$2, ..., f_n2; $d_1$1, $d_2$1, ..., d_n1] and [$f_1$2, $f_2$2, ..., f_n2; $f_1$3, $f_2$3, ..., f_n3; $d_1$2, $d_2$2, ..., d_n2], a new sample group can be generated by merging bearing displacement [$f_1$1, $f_2$1, ..., f_n1; $f_1$3, $f_2$3, ..., f_n3; $d_1$1 + $d_1$2, $d_2$1 + $d_2$2, ..., d_n1 + d_n2]. 'N' groups of adjacent samples can create ($\frac{n^2}{2} - \frac{3}{2}n + 1$) groups of new samples, thereby expanding the number of measured samples to a certain extent.

2.4. Transfer Learning Method

There are four main transfer learning methods: instance-based transfer learning, feature-based transfer learning, parameter-based transfer learning, and relation-based transfer learning. Given the resemblance between the design shafting model and the actual shafting model, the samples obtained from the two models had no missing items and shared a certain common connection. Consequently, this research employed two transfer learning methods: sample-based and model-based.

2.4.1. Sample-Based Transfer Learning

The sample-based transfer learning method reuses data samples according to certain weight generation rules, so as to achieve the purpose of improving results. The simulation sample is used as the source data, the measured sample is used as the target data, and the source data and the target data are weighed by weight generation rules. The weight is calculated according to Equations (1) and (2):

$$y_i = N_i / \sum_i^n N_i \tag{1}$$

In Equation (1), y_i is the proportion of samples of a certain type in the total samples; N_i is the number of samples of a certain type.

$$W(y_i) = 1/\log(C + y_i) \tag{2}$$

In Equation (2), $W(y_i)$ is the weight of a certain type of sample; C is a constant and $C > 0$.

The sample weight is added to the final loss function, and the influence of the measured samples on the loss function is adjusted to improve the attention of the neural network model to a small amount of measured data [30], and finally build an accurate actual shafting bearing load and displacement relationship. With the shafting alignment process, new measured data can be obtained and the measured sample set can be expanded, further improving the accuracy of the neural network model.

The loss function is calculated according to Formula (3), and the loss function adding sample weight is calculated according to Formula (4):

$$E = \frac{1}{2N}(T - Y)^2 = \frac{1}{2N}\sum_{i=1}^{N}(t_i - y_i)^2 \tag{3}$$

In Equation (3), T is the real result; Y is the network output result; i is the i-th data; t_i is the real result corresponding to the i-th data; y_i is the network output result corresponding to the i-th data; N is the number of training samples; $T - Y$ is the error between each training sample and the real result.

$$E' = \frac{1}{2N}(T - Y)^2 * W(y) = \frac{1}{2N}\sum_{i=1}^{N}(t_i - y_i)^2 * W(y_i) \tag{4}$$

In Equation (4), E' is the weight-adjusted loss function.

2.4.2. Model-Based Transfer Learning

The primary aim of this method is to identify shared parameter information between the source and target domains, facilitating migration between the two. The model training process is divided into two parts: universal learning and feature learning. Fundamentally, this method involves initializing model parameters based on acquired knowledge rather than relying solely on random initialization [31]. It effectively combines static experimental simulation data with real-time information, enabling model adaptation to dynamic environments and the construction of accurate models [32,33].

In the context of shafting alignment, certain model parameters can be shared between the design shafting bearing load-displacement relationship and the actual shafting bearing load-displacement relationship due to their correlation. These model parameters encompass knowledge acquired from the simulation sample set, some of which is also applicable to the measured sample set. Consequently, parameter sharing becomes feasible through this approach, allowing for the sharing of specific parameters.

Typically, the first layer is not particularly related to the specific dataset, while the last layer of the network is closely related to the selected dataset and its task goals. The features extracted by the first layer are referred to as general features, whereas those obtained by the last layer are termed specific features [34]. Given discrepancies between design shafting and actual shafting, the output layer of the design shafting neural network model is closely related to the simulation sample set. Therefore, utilizing output layers from the design shafting neural network models for actual shafting models is not suitable. Consequently, adjustments focus solely on specific feature layers, while other layers remain unchanged during this method. In instances of suboptimal performance, further fine-tuning of the remaining layers can be undertaken by reducing the initial learning rate to one-tenth of the value used during initial training.

The model-based transfer learning process is depicted in Figure 5, and involves copying some parameters from the design shafting load and displacement relationship neural network model as parameters of the actual shafting load and displacement relationship model. Subsequently, the network parameters of the output layer are randomly initialized. By training using measured sample sets, an accurate bearing load and displacement relationship model for actual shafting can be obtained through this approach.

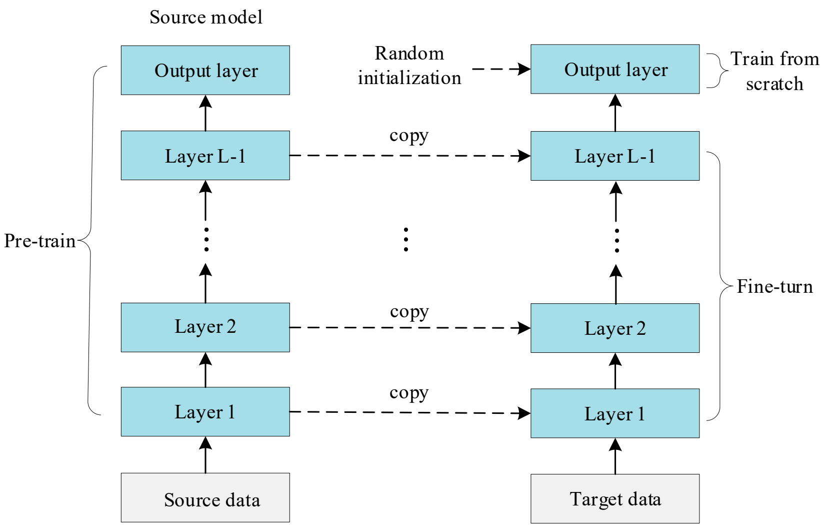

Figure 5. Schematic diagram of model-based transfer learning.

2.5. Calculating the Bearing Displacement Values

Based on the neural network topology constructed in Section 2.2, both measured loads and design loads for each bearing were input into the neural network model, and the model output was a set of bearing displacement values.

3. Application Examples

3.1. Research Object

The propulsion shafting of a large cruise rescue ship was taken as the research subject. The total length of the shafting was 43.8 m, including three intermediate shafts with lengths of 8 m, 8 m, and 7.461 m. The main shaft section of each intermediate shaft had an outer diameter of 305 mm and an inner diameter of 120 mm. The stern shaft had a length of 18.146 m, with its main shaft segment having an outer diameter of 350 mm and an inner diameter of 120 mm. Positioned in front of the stern shaft was the propeller, while behind the intermediate shaft lay the main engine crankshaft. This multi-support shafting consisted of four intermediate bearings. The structural diagram can be seen in Figure 6.

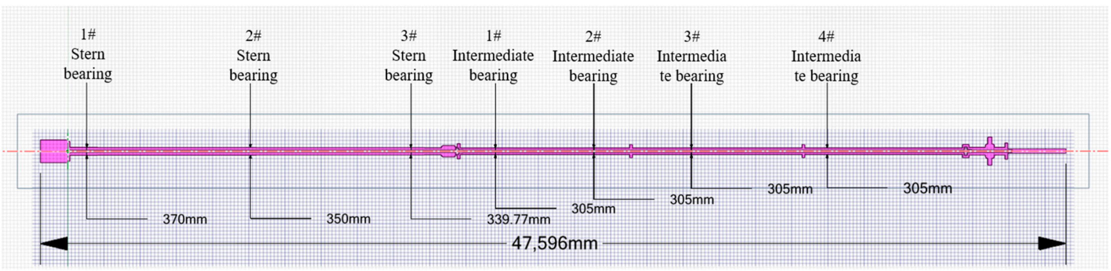

Figure 6. Schematic diagram of propulsion shafting structure.

All design parameters were meticulously known, enabling the creation of a comprehensive numerical model using finite element software. As per the specifications delineated in the shafting design calculation sheet, constraint conditions, load, and displacements were applied to each part of the shafting model. Displacement constraints were specifically applied to the three stern bearings in accordance with their designated heights. Moreover, the section of the shafting tail extending beyond the hull was treated as a free end. A concentrated force equivalent to the weight of the propeller was applied at the propeller installation position and the buoyancy of the propeller was applied, accounting for gravity across the entire shafting. To accurately replicate bearing support characteristics, axial and radial springs were incorporated at the contact surface of each intermediate bearing with the shafting. The stiffness of the these springs replaced that of the entire bearing support system. The radial springs simulated actual bearing support behavior. When determining adjustments for bearing displacement, only radial displacement at intermediate bearings was considered by modifying the length of corresponding radial springs. Additionally, an axial spring, possessing sufficient elastic modulus and approximate rigidity, was introduced to confine the overall axial displacement of the entire shafting [20].

By substituting the bearing design height into the model for computation, the finite element analysis revealed a maximum error of 4.74% between the intermediate bearing load and the design load. The minimum discrepancy was 0.77%, with an average of 2.73%. These values aligned with the specification requirements, affirming the model's adherence to the design criteria and its reliability for both calculation and simulation samples.

Critical factors influencing shafting alignment were the stern bearing and the main engine, where positioning errors and installation deviations significantly impact the alignment process. Table 1 compares various deviation scenarios between the designed shafting and the actual shafting. Notably, positive positioning error refers to a deviation in the vertical upward direction, while positive axial deviation denotes a stretching direction.

Table 1. Different error scenarios.

Serial Number	Deviation Factors
Case 1	Main engine positioning deviation + 2 mm
Case 2	Main engine axial mounting deviation + 5 mm
Case 3	Main engine positioning deviation + 2 mm and stern shaft positioning deviation − 0.5 mm
Case 4	Main engine positioning deviation + 5 mm, stern shaft positioning deviation − 2 mm and main engine unit axial installation deviation + 10 mm

The actual shafting in this research was simulated by modifying the model parameters according to the deviation in Table 1 on the basis of the design shafting numerical model. This actual shafting numerical model was employed to simulate displacement adjustment processes, with its calculated data serving as measured data for the actual shafting.

3.2. Analysis Ideas

The calculation methods of displacement values investigated in this article are shown in Table 2. The primary focus lies in investigating the efficacy of two transfer learning methods across different shafting error scenarios. For comparative purposes, Method 1, utilizing the design shafting bearing load and height relationship model, is introduced. This method employs simulated samples to train a neural network, generating the design shafting bearing load and displacement relationship model. Subsequently, it calculates displacement values based on the current bearing measurement load and design load [20]. To ensure a fair comparison, each deviation scenario starts from identical initial conditions. The alignment cycle for shafting adjustments is not based on load checking but on a predetermined number of adjustments as the exit condition.

Table 2. Method type.

Serial Number	Method
Method 1	Bearing load and height relationship based on the design shafting
Method 2	Bearing load and displacement relationship modified based on sample transfer learning
Method 3	Bearing load and displacement relationship modified based on model transfer learning

3.3. Construction of Transfer Learning Model

The design shafting numerical model was constructed, setting the height change range of each intermediate bearing at ±2 mm, with a displacement interval defined as a minimum unit of 0.1 mm [35]. For this research, a total of 1900 sets of simulation training samples were generated, with 1800 sets allocated for training samples and an additional 100 sets serving as test samples.

Considering the characteristics of the research subject, the neural network model took as inputs the load values of the four intermediate bearings before and after displacement, while producing the corresponding displacement values for these bearings as outputs. The BP algorithm selects the logarithmic S-type logsig function as the hidden layer node transfer function, with the linear Purelin function serving as the transfer function for the output layer nodes (expressed as y = x). The training times were 10,000, the learning rate was 0.05, and the number of nodes in the intermediate double hidden layers was set to 15. Post-training assessment revealed an average error of 0.40% in the test data.

These results affirm that the neural network model trained extensively on simulation data exhibited superior learning capabilities, effectively portraying the design shafting bearing load and displacement relationship. This model served as the fundamental model for transfer learning in Method 2. When constructing the fundamental model for transfer learning in Method 3, it was crucial to optimize and adjust the number of neurons in proximity to the output layer. This adjustment significantly influenced its efficacy, requiring meticulous optimization. After rigorous calculation, the impact of varying neuron counts in this layer on the calculation error of the migrated model was confirmed and is graphically depicted in Figure 7. Notably, the number of 5 neurons demonstrates the smallest error. Consequently, the number of neurons in the hidden layer adjacent to the output layer is refined from 15 to 5 in this method, while other parameters remain constant.

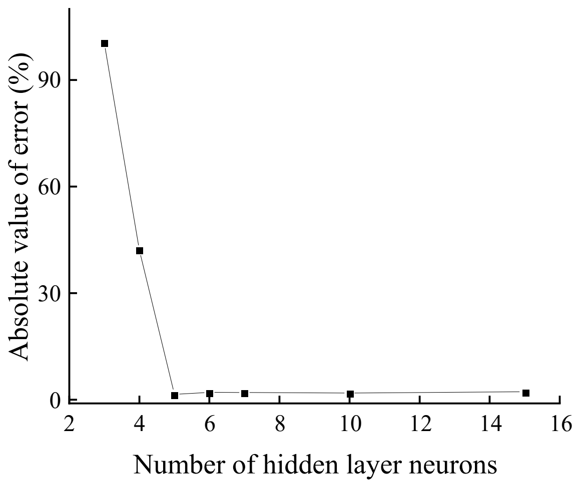

Figure 7. The impact of the number of hidden layer neurons near the output layer on Method 3.

3.4. Application Effect

Figures 8–11 illustrate the effects of the four scenarios on the neural network performance. In each figure, (a), (b), and (c) respectively represent the variation of the measured load error of each intermediate bearing with the number of bearing displacement adjustments. The final error comparisons between the measured load and design load for each scenario are presented in Figure 12; the logarithmic coordinate system is employed for the purpose of comparison.

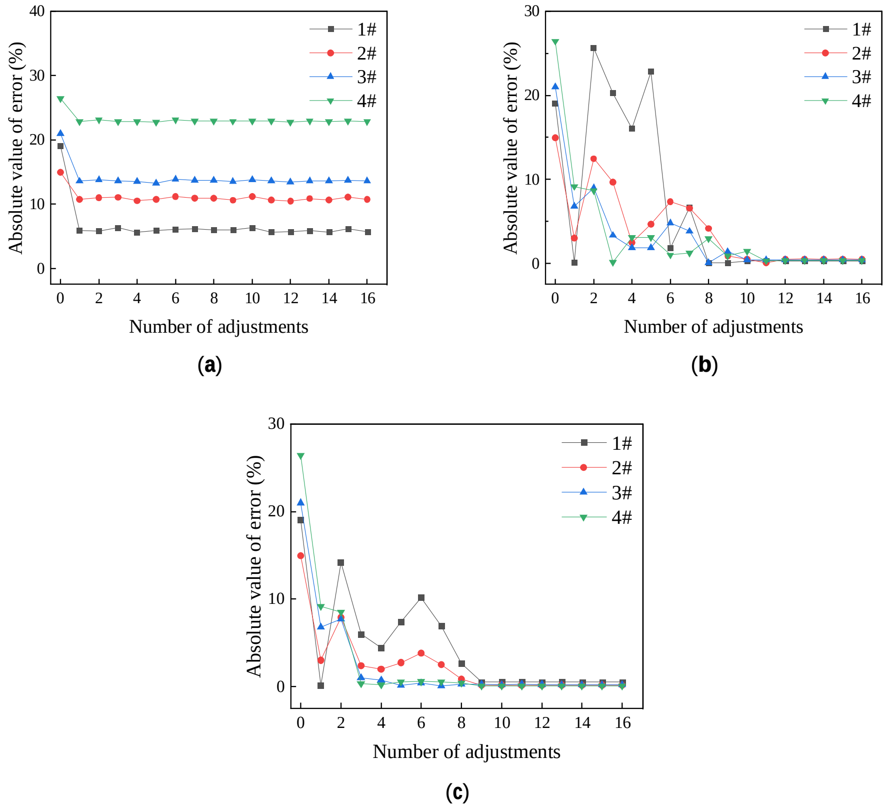

Figure 8. Application effects of three methods in Case 1. (**a**) Method 1; (**b**) Method 2; (**c**) Method 3.

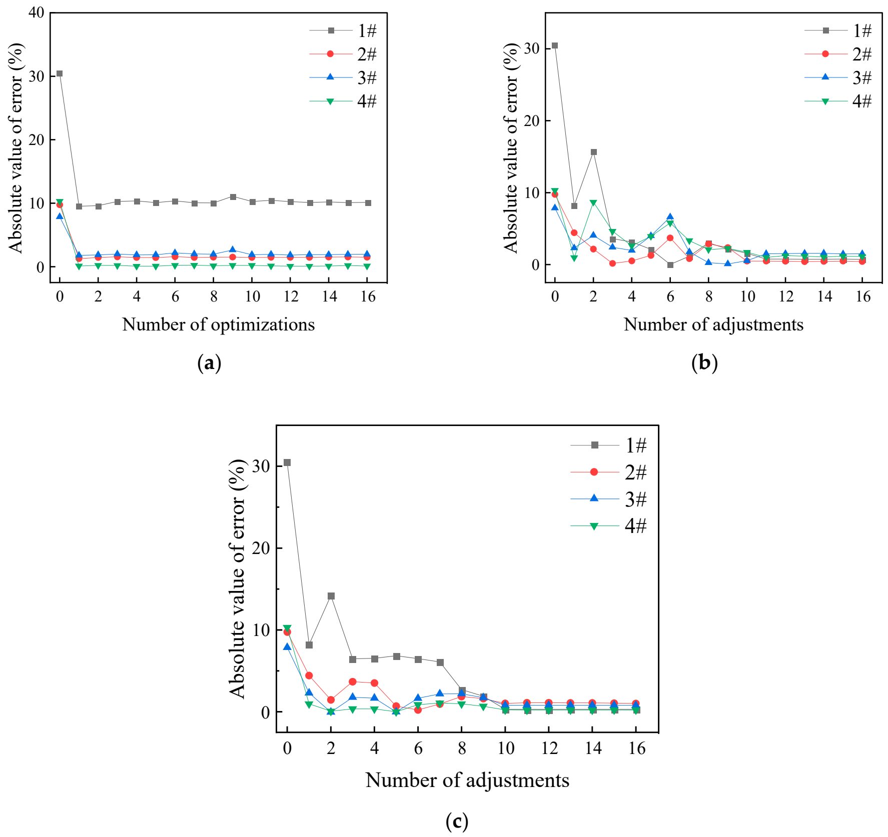

Figure 9. Application effects of three methods in Case 2. (**a**) Method 1; (**b**) Method 2; (**c**) Method 3.

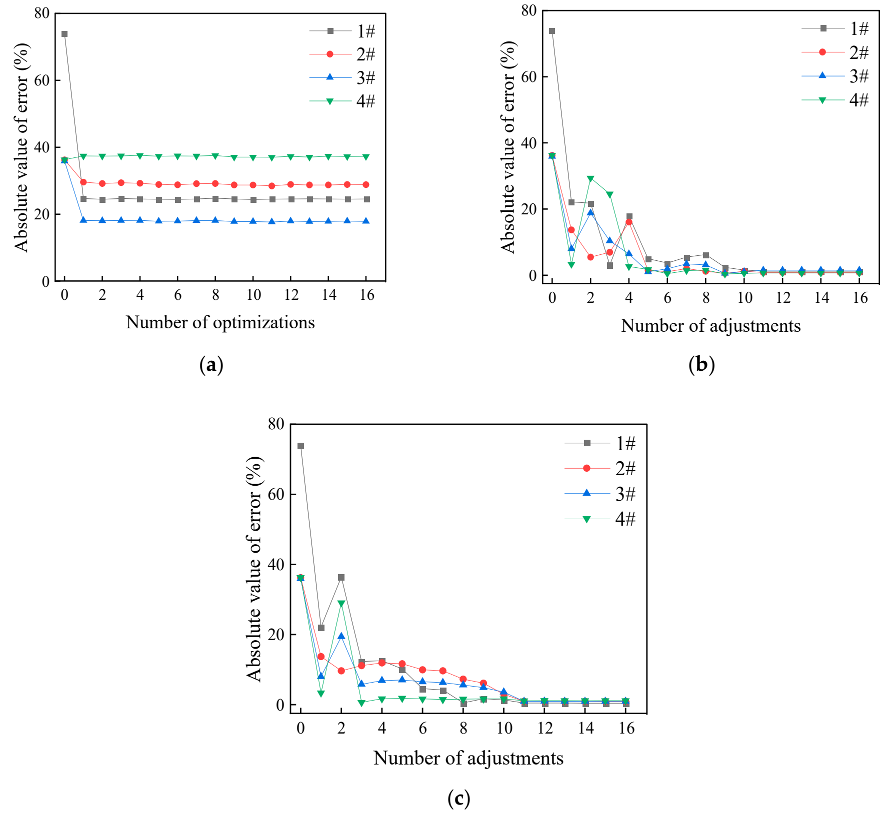

Figure 10. Application effects of three methods in Case 3. (**a**) Method 1; (**b**) Method 2; (**c**) Method 3.

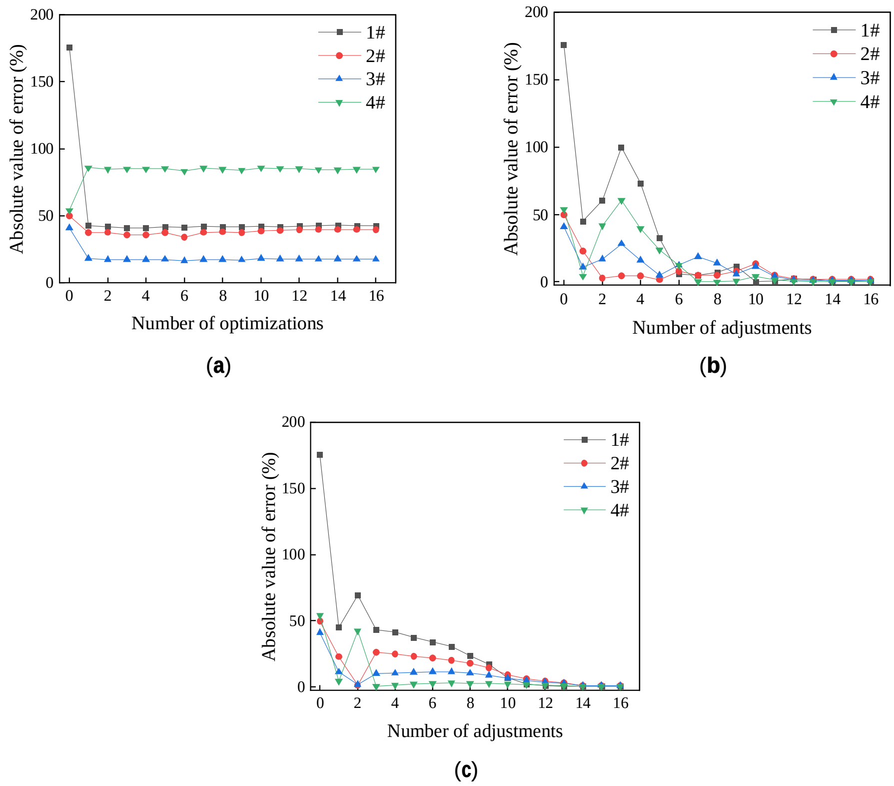

Figure 11. Application effects of three methods in Case 4. (**a**) Method 1; (**b**) Method 2; (**c**) Method 3.

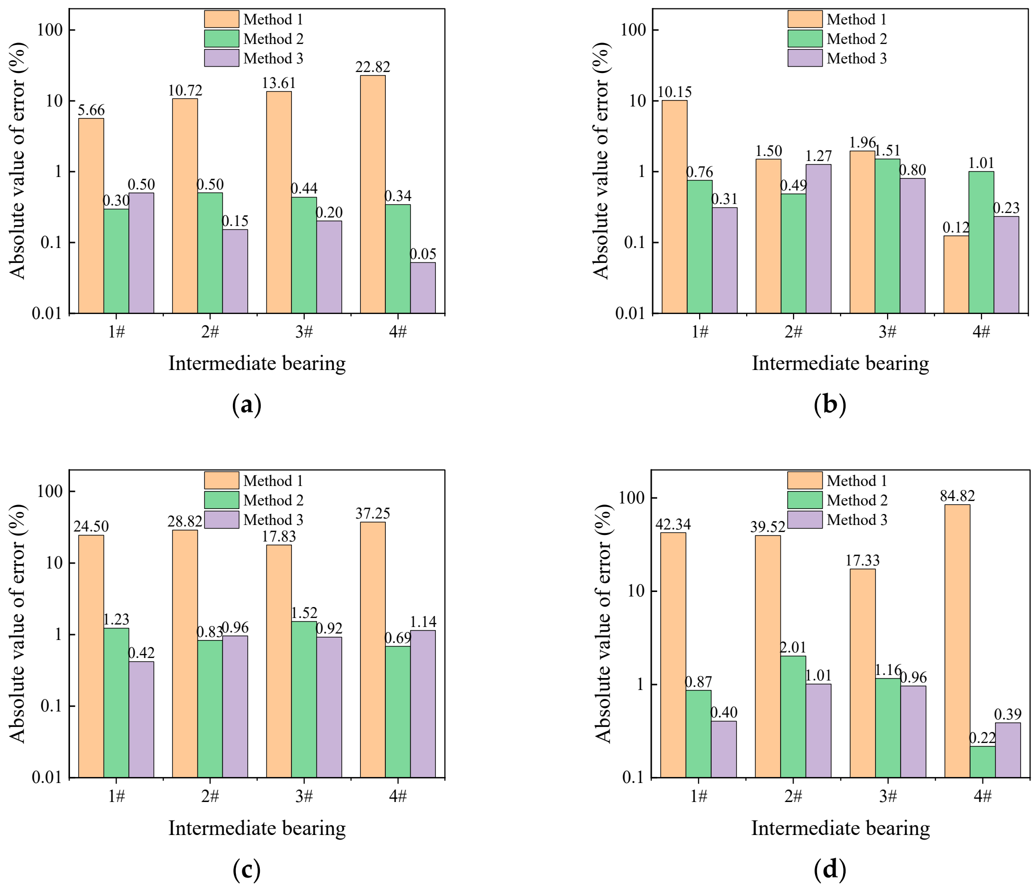

Figure 12. Comparison of final errors in various scenarios. (**a**) Comparison of errors in Case 1; (**b**) Comparison of errors in Case 2; (**c**) Comparison of errors in Case 3; (**d**) Comparison of errors in Case 4.

The effectiveness of Method 1 remained consistent across all scenarios. As the error escalated, so did the deviation between bearing measurements and design loads. Except for in scenario 2, deviations between the design shafting and the actual shafting led to bearing load errors exceeding the allowable limit (±20% of the design load) in all three scenarios. Throughout the shafting adjustment, while neural network errors maintained relative stability, the calculated measured bearing loads displayed minimal fluctuation. Consequently, Method 1 lost its capacity to adjust bearing loads.

In contrast, Method 2 consistently demonstrated effective application across every scenario as bearing measured loads gradually approached design levels during shafting adjustments. Across the four scenarios, the error between each intermediate bearing measured load and the design load remained below 10% at the 6th, 3rd, 5th, and 10th adjustments, respectively, reaching a steady state after the 11th, 11th, 11th, and 14th adjustments. The maximum error after stabilization was 2.01%, the minimum was 0.22%, and the average was 0.87%, significantly lower than those seen with Method 1.

Method 3 exhibited commendable effectiveness across all scenarios as it gradually aligned the measured bearing loads with the design levels during shafting adjustments. Notably, compared to Method 2, Method 3 demonstrated milder fluctuations overall. In the four scenarios, the error between each intermediate bearing measured load and the bearing design load was consistently below 10% at the 5th, 7th, 8th, and 11th adjustments respectively, stabilizing after the 10th, 12th, 12th, and 13th adjustments. Upon stabilization, Method 3 recorded a maximum error of 0.97%, a minimum value of 0.052%, and an average of 0.39%. Method 3 achieved a further reduction in error after stabilization compared to Method 2, positioning the obtained measured bearing load closer to the design bearing load.

The stability, rapidity, and accuracy of all three methods in the shafting adjustment process are summarized in Table 3.

Table 3. Comparison of effects of various methods.

Type	Iterative Stability	Rapidity	Accuracy
Method 1	Less fluctuation	Only one adjustment is required	Major error
Method 2	The error fluctuates is large	Achieving stability is slightly slower but requiring less adjustments to make the deviation less than 10%	High accuracy when the deviation is small; when the deviation is large, the accuracy decreases
Method 3	Relatively stable with slight fluctuations	Achieving stability is slightly faster but requires more adjustment to make the deviation less than 10%	Maintaining high accuracy in various deviations

4. Discussion

(1) Method 1 disregards the discrepancy between the designed shafting and the actual shafting, and can only calculate the displacement values based on the design bearing load and displacement relationship model, according to the bearing measured load and design load. Essentially, it relies on an iterative trial-and-error approach using the alignment path obtained from the design shafting model, without considering data information or experiential knowledge acquired during learning about actual bearing adjustment process. Moreover, when there was a significant initial bearing load error, it lacked the ability to reduce this error in subsequent shafting adjustment processes.

(2) Method 2 and Method 3 are based on the design shafting bearing load and displacement relationship, using measured data obtained from the actual shafting through the bearing alignment process for transfer learning. This enabled them to rectify the actual shafting bearing load and displacement relationship model, gradually enhancing the accuracy of acquired bearing displacement values. Both methods effectively indicated the direction for shafting adjustment and correction, addressing issues commonly encountered in traditional shafting adjustment methods such as difficulty in identifying adjustment patterns, loss of adjustment direction, and increased deviation in bearing load. Consequently, they improved both quality and efficiency in shafting alignment. Compared to Method 2, Method 3 achieved stability more rapidly while further improving accuracy of bearing displacement values after reaching stability. Moreover, it maintained high accuracy under various error conditions. The simulated sample and the measured sample were always combined in the iteration process of Method 2, but the error between them was difficult to completely eliminate through weight, resulting in a slightly lower accuracy of the bearing displacement values after stability. Method 3 solely employs measured samples for training a new fully connected layer, which not only required less time but also yielded a trained model closer to reality, thereby ensuring higher accuracy of displacement values.

(3) Increasing deviation between the design shafting and the actual shafting demanded more adjustments for Method 2 and Method 3 to achieve stability. Consequently, the number of displacement adjustments required for each intermediate bearing load error to reach 10% gradually rose. Moreover, due to a small proportion of measured data during early stages of shafting alignment, Method 2 exhibited fluctuations in bearing measured load.

(4) Neither Method 2 nor Method 3 completely eliminated the discrepancy between the bearing measured load and the design load. This is because the design load is calculated based on the design shafting, while shafting alignment involves adjusting bearing displacements for actual shafting. Consequently, the deviation between the design load and the actual bearing is the reason why the bearing measured load cannot be equal to the design load.

5. Conclusions

In this research, under the conditions of incomplete data of actual shafting during shafting alignment, transfer learning was used to construct the actual shafting bearing load and displacement relationship based on the design shafting model and limited actual shafting measured data. According to the application effects of four scenarios with different degrees of main engine positioning deviation and stern shaft positioning deviation, the following conclusions were obtained:

(1) The multi-support shafting displacement values calculation method based on transfer learning effectively utilized design shafting existing knowledge and the measured data from the actual shafting displacement adjustment process. This progressively improved the accuracy of the obtained displacement values, enhancing shafting alignment quality and efficiency.

(2) While the numerical simulation validates the method's superiority, further research is required to enhance efficiency and minimize the necessary iterations.

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