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Deep Learning for Marine Engineering Project Quality SPC

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Abstract: In the prefabrication construction of marine engineering, the use of SPC method is an important means to ensure quality stability. It can timely alarm and take measures for abnormal phenomena in the process of marine construction and management, so as to keep the process at a recognized quality level and improve the quality of marine engineering pass rate, save a lot of cost, use quality to ensure benefits, and achieve a win-win situation for reputation and profit. In order to solve the shortcomings of the existing research on the quality SPC of marine engineering projects, this paper discusses the concept of the control chart structure and steps of the quality SPC of marine engineering projects and the functional equation of SPC, and aims at the deep learning-based marine engineering projects. Project data and parameter settings for quality SPC applications are briefly introduced. In addition, the workflow design of the SPC structural model of marine engineering project quality based on deep learning is discussed, and finally the application of deep learning in marine engineering project quality SPC in offshore engineering pile-pipe welding is compared and analyzed. The recognition rate of unqualified mean changes in offshore engineering pile-pipe welding occurred in the quality SPC process is much higher than that of the LR and AR models, and the recognition rate of deep learning after the quality SPC coefficient of 3 both reaches 100. The recognition rate does not exceed 20, which further verifies that deep learning has a high recognition rate for unqualified mean changes in offshore engineering pile-pipe welding that occur in the quality SPC process.

1. Introduction

Due to the continuous and rapid development of ocean engineering, the importance of SPC in ocean engineering quality management has been better reflected. SPC needs to collect a large amount of data in real time, and then analyze and calculate the data through deep learning. In the management work, the unique function of SPC makes it an indispensable part.

Nowadays, more and more scholars pay attention to the research of various technologies and platforms in the quality SPC of marine engineering projects, and through practical research, they have also achieved certain research results. Snh A proposed Statistical Process Control (SPC) as a tool for quality and process control. It is the pursuit of workload minimization and the safety assessment of the process. Due to ever-increasing quality requirements and increasing competition, product quality must be continuously improved. In order for the SPC to function properly, certain criteria must be met. For example, in the design part of the product, it should be understood that different characteristics should be regarded as the quality center link. Snh A conducted a survey of the technical organization of an international company and identified the necessary preparations for the adoption of SPC in the company. Company characteristics and selection of SPC measurement techniques are discussed [1]. Kamikawaji Y believes that by monitoring the output error process input data of the product planning process and the target, the quality of the product can be guaranteed. SPC stands for Statistical Process Control and it is used to monitor a process to identify the cause of any variation in product quality. EPC involves regulation of product input to maintain product quality output up to standard using different controllers. Experiments have shown that the combination of SPC and EPC can effectively reduce the failure rate of products. Its main goal is to redesign the production and quality control system of a processing company through a controller (EPC) to achieve the goal of simultaneous optimization using a control chart (SPC) to monitor the system [2]. S, Subhashini calculated the combined indicators of pollution potential (PP) and self-purification capacity (SPC) of river waters within the boundaries of the hydrological region. Wastewater volume and population density in the catchment area (anthropogenic component of pollution), sediment load (natural component of pollution). The natural environment of the watershed, such as the role of lake topography in the self-purification of the river, has been used to calculate the SPC. The water quality entering the sea is the result of the ratio of the proposed comprehensive indicators. Based on the quantitative ratio of PP and SPC, the basin was divided according to the degree of negative impact of river water on the water quality of the White Sea [3]. Although the existing research on the quality SPC of marine engineering projects is very rich, the research on the application of the quality SPC of marine engineering projects based on deep learning is still insufficient.

Therefore, in order to solve the existing problems in the research on the quality SPC of marine engineering projects based on deep learning, this paper firstly introduces the functional equation steps of the quality SPC of deep learning and the concept of quality SPC for marine engineering projects, and then discusses the marine engineering project quality SPC based on deep learning The project data and parameter setting analysis of engineering project quality SPC application, and finally design the application model architecture of offshore engineering project quality SPC based on deep learning, and carry out the application of offshore engineering project quality SPC in pile-pipe welding based on deep learning technology. Experiments and final experiments show the feasibility of the deep learning-based ocean engineering project quality SPC research proposed in this paper.

2. Ocean Engineering Project Quality SPC Based on Deep Learning

2.1. Quality SPC for Deep Learning

The SPC of deep learning refers to the average of the number of out-of-control samples [4]. The calculation formula of the out-of-control sample recognition rate of deep learning BPC is as follows:

$$SPC = \frac{1}{\beta} \tag{1}$$

Among them, β is the possibility that the mean SPC of the quality of any marine engineering project will be out of control in the process [5]. There are two cases of SPC: SPC0 in the quality-controlled process of marine engineering and SPC1 in the out-of-control process [6].

SPC0 refers to the average value of the number of samples that pass before the first out-of-control sample occurs when the quality process of marine engineering is controlled [7]. The calculation formula is as follows:

$$SPC_0 = \frac{1}{\beta} \tag{2}$$

For the quality SPC of deep learning with A as the control limit, the probability of occurrence of Type 1 error is 0.001 [8]. Therefore the SPC0 of a normal identification process is equal to 270 [9]. That is to say, for a normal marine engineering quality SPC identification process, there will be an out-of-control situation in every 270 samples on average. Usually, the larger the SPC0 value, the better [10].

SPC1 is defined as the average number of samples of normal marine engineering quality SPC before an out-of-control point is detected when the process is out of control. The calculation formula is as follows:

$$SPC_1 = \frac{1}{1-\varepsilon} \tag{3}$$

Among them, ε is the probability that the SPC of the normal marine engineering quality cannot be found out of control in the first sample after the SPC of the normal marine engineering quality is out of control [11]. Usually, it is hoped that the smaller the SPC1, the better, so that the normal marine engineering quality SPC can be found out of control in time and the process can be corrected [12].

2.2. Ocean Engineering Project Quality SPC

(1) Quality SPC control chart structure

The most common method of SPC is the control chart, which is a very simple SPC chart [14]. The traditional control chart usually has a center point (CL), an upper control limit (UCL) and a lower control limit (LCL), and the center line is usually the average value of the whole process being measured [14]. The upper and lower control lines of the center point are calculated by the computer according to a set of information collected, so they cannot be arbitrarily determined artificially. The upper and lower control limits are set [15]. As long as the variability of the quality inspection process is kept within limits, the inspection can be considered normal. Beyond any control limit, the change is not normal [16].

(2) Steps of Quality SPC Control Chart

The steps of the SPC control chart are as follows:

1) Collect data and report in the form of subgroups with constant data sample size, the subgroups usually include a continuous product, and the subgroups are drawn periodically, including the subgroup size and frequency [17].

2) Establish control charts and record raw data.

3) Calculate the statistic to choose the scale of the control chart [18].

4) Draw dotted lines.
5) Analyze and control the process

3. Research on SPC Survey of Marine Engineering Project Quality Based on Deep Learning

3.1. SPC Project Data of Marine Engineering Project Quality Based on Deep Learning

Each pile pipe of the offshore engineering pile pipe structure is 105m long and needs about 24 counterparts. For the pile pipe, select the number of 50 pairs of passages as the number of statistical subgroups, that is, A=50; each passage is divided into four parts, check the two items of misalignment and clearance, a total of 8 points (that is, the size of the subgroup is taken as 8), and collect them. As the preliminary data for establishing the control chart of the number of unqualified offshore platforms. Non-conformance point B is defined as a check point that exceeds marine quality regulations. In this paper, a continuous inspection is carried out on the counterpart process of the piles and pipes under construction, and the data of the unqualified points are recorded, as shown in Table 1:

Table 1. Unqualified data for pile-pipe structures

A	1	2	3	4	5	6	7	8
B	2	1	3	5	6	4	2	1
A	9	10	11	12	13	14	15	16
B	1	3	5	2	4	3	2	1
A	17	18	19	20	21	22	23	24
B	2	5	4	3	1	2	3	5

3.2. SPC Parameter Setting of Marine Engineering Project Quality Based on Deep Learning

The optimal parameters of the deep learning model are as follows: the number of hidden layer nodes is 13, the number of layers is 5, the learning rate is 0.01, and the optimizer selects BPG. In order to compare the quality SPC test results of marine engineering projects more effectively, and to prevent the experimental inaccuracy caused by inconsistent parameters, the parameter selection of deep learning and LR should be consistent with the parameter selection of AR. The parameter settings of the deep learning model, LR and AR models are shown in Table 2:

Table 2. Deep learning parameter settings

Name	Parameter
Number of neurons	12
Activation function	Sigmoid
Loss function	MSE
Detection rate	0.02
Optimization	BPG

4. Research on SPC Application of Marine Engineering Project Quality Based on Deep Learning

4.1. Structure Design of Quality SPC Detection of Marine Engineering Project Quality Based on Deep Learning

According to the neural network in deep learning and quality SPC control chart structure and control chart steps and the parameter settings of the neural network in deep learning, the structural design of the detection process of marine engineering project quality SPC based on deep learning in offshore engineering pile-pipe welding is carried out, the specific structural design is shown in Figure 1.

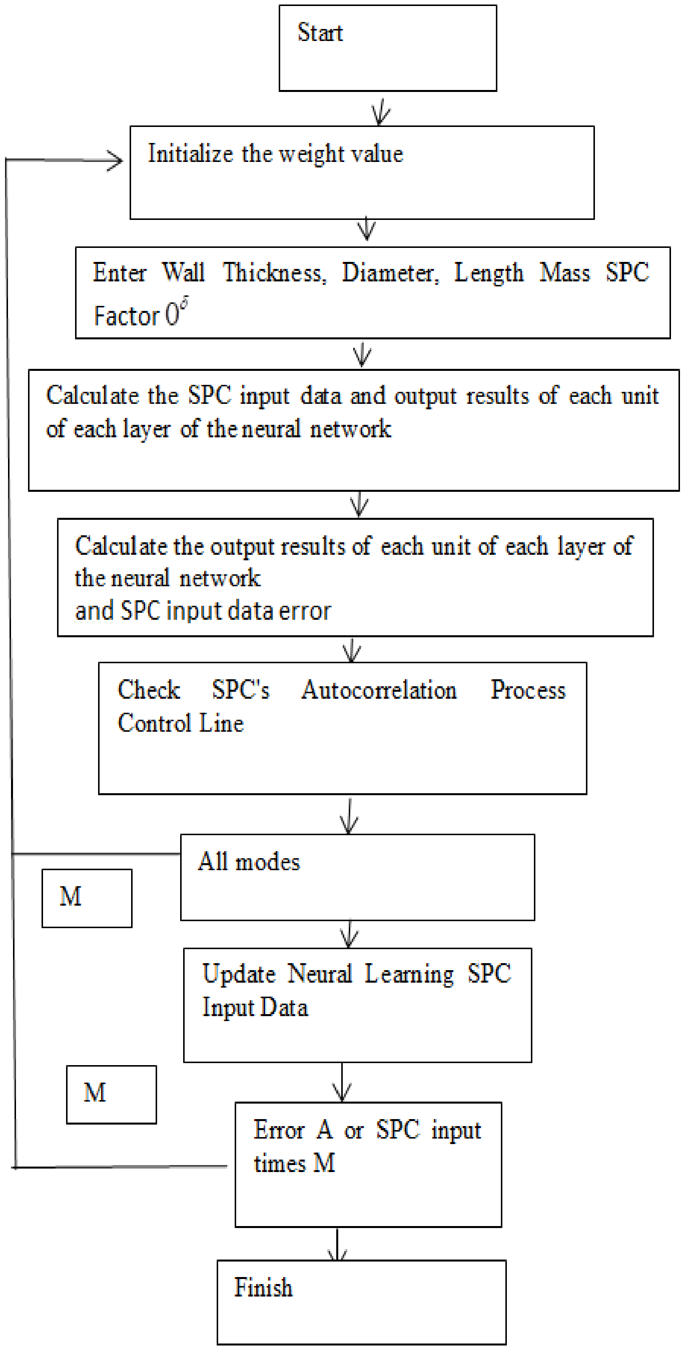

Figure 1. Deep learning-based structural model for marine engineering project quality SPC identification

The specific steps of SPC detection of marine engineering project quality based on deep learning are as follows:

(1) Initialize the weight values of the neural network in deep learning.

(2) Given an ocean engineering project quality SPC input data sample, and give the associated expected output results

(3) Input the SPC coefficient 0^{δ} of wall thickness, diameter, length and mass, and obtain the output result of each layer according to a certain algorithm.

(4) Calculate the gap between the output results of each layer and each unit of the neural network in the deep learning and the input data of the marine engineering project quality SPC.

(5) Check whether the input data of the marine engineering project is within the autocorrelation process control line of the quality SPC. If it exceeds, go back to step 1 and recalculate.

Determine whether the output results meet the quality SPC input data samples of marine engineering projects. If the quality SPC input data sample index of marine engineering projects is met, the training is terminated. If it does not meet, start from (1) again, which is an iterative training process.

4.2. Application of Quality SPC for Marine Engineering Project Quality Based on Deep Learning

In this paper, the neural network generated by deep learning is used to compare the output results of the LR and AR models of the inspection results of the wall thickness, diameter, length and quality SPC in the welding of piles and pipes in marine engineering. The input data of the 8 groups of autocorrelation process mean $0^{\delta};1^{\delta};2^{\delta};3^{\delta};4^{\delta};5^{\delta};6^{\delta};7^{\delta};8^{\delta}$ order leap-type mean mutation. The 0^{δ}-mean change means that the process is in a steady state and no mean change occurs. The reason why we need to consider the ability of deep learning to identify the autocorrelation process in a steady state (no mean change) is to test the ability of deep learning to identify the first type of errors in the quality SPC of foreign engineering projects. The specific experimental comparison data is shown in Figure 3 show.

Table 3. Deep learning and LR and AR model recognition rate data

0^{δ}	LR	AR	Deep learning
1	97.89	96.78	99.87
2	7.98	5.78	87.67
3	8.78	9.78	100
4	16.56	8.89	100
5	10.34	9.67	100
6	7.67	8.34	100
7	9.45	10.23	100
8	10.55	7.49	100

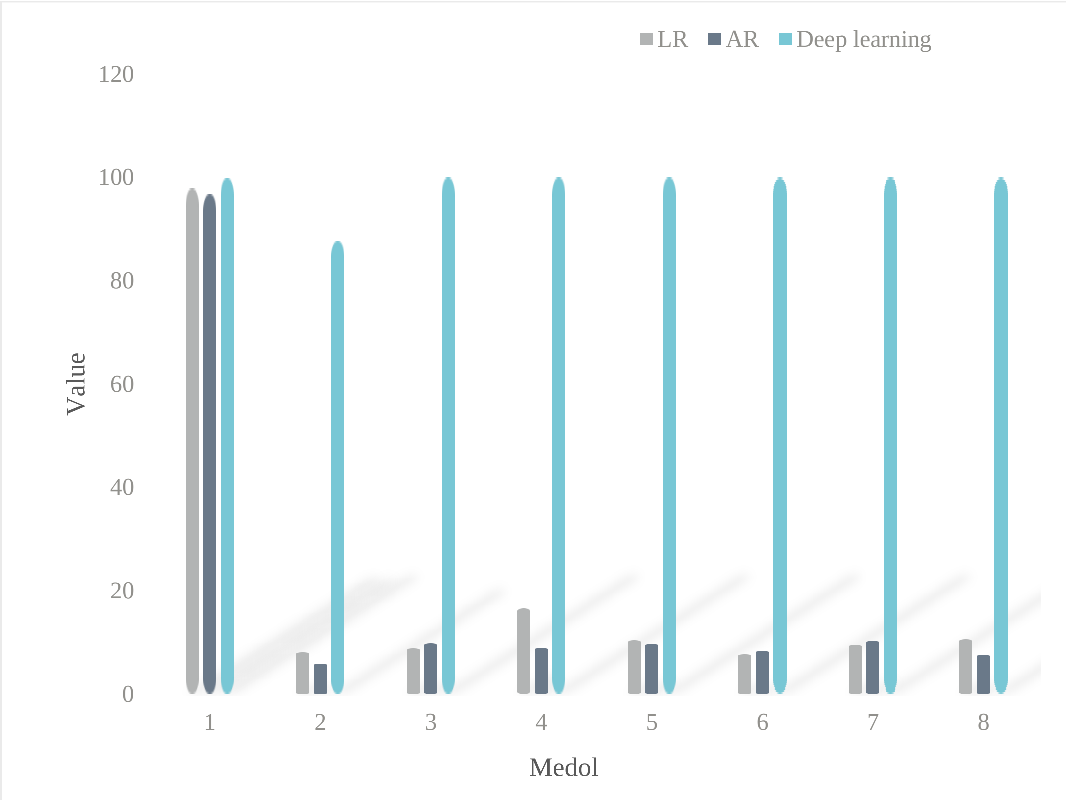

Figure 2. Comparison of recognition rates of deep learning and LR and AR models

As shown in Figure 2, when the wall thickness, diameter, and length mass SPC coefficient δ in the pile-pipe welding in offshore engineering is from 1 to 8, the recognition rate of deep learning for the 1^{δ}, 2^{δ}, and 3^{δ} order mean changes in the quality SPC process. Much higher than the LR and AR models. For small changes of 1^{δ} in the process, the recognition rate of deep learning reaches more than 80%. The LR and AR models are basically unable to effectively identify such small changes. When the correlation is between 1 and 3, the recognition rate is less than 10%. It can be seen that the deep learning is much more effective than the LR and AR models for the detection of changes in the process mean 1^{δ}.

5. Conclusion

Therefore, in order to enrich the research on the quality SPC of marine engineering projects based on deep learning, this paper first briefly introduces the quality SPC function equation of deep learning and the concepts of the structure and steps of the quality SPC control chart of marine engineering projects, and then discusses the deep learning of marine engineering projects. Based on the analysis and discussion of engineering project quality SPC technology, the project data and parameter settings of marine engineering project quality SPC based on deep learning are investigated and designed. Secondly, the design and analysis of the model architecture of the deep learning marine engineering project quality SPC application is carried out, and finally the experimental data analysis is carried out for the application of the deep learning marine engineering project quality SPC designed in this paper in the offshore engineering pile-pipe welding, and the final experimental results are verified. In this paper, the superiority of SPC for marine engineering project quality based on deep learning.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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