A Neural Network Based Defect Prediction Approach for Virtual High Pressure Die Casting

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Abstract: Prediction of defects is important to effective process planning for high pressure die casting (HPDC). Current computer aided engineering (CAE) methods of defect prediction are widely used by experienced engineers in industry. However, it is hard for novices to image and understand the underlying relationship between the process and defects. To bridge the gap between training and onsite applications, this paper presents a neural network based defect prediction approach (DPA) for virtual HPDC, and details of the DPA development and its implementation in VR are explained. Moreover, a Virtual HPDC Lab is developed as the case study to demonstrate the functionality of DPA proposed, and the result survey verified that the virtual lab with DPA is very much effective for learning and training of HPDC.

1. Introduction

High pressure die casting (HPDC) is an important metal manufacturing process, which has enabled mass production of cast alloy components with high dimensional accuracy and great efficiency[1]. For a process engineer to use HPDC, it is not only takes time to learn the process and the operation of the die-casting machine, but also needs to understand the influence of casting parameters on defects. However, due to resources, and security factors, both scholars and workers have few opportunities to conduct number of field operations to accumulate experiences. Hence, it is necessary to improve the effectiveness of learning and training for HPDC.

Virtual reality (VR) is a three-dimensional (3D), interactive virtual environment rendered, which can restore the real scene[2] in real time by computer[3], and simulates operations without causing personal injury and equipment wear[4], so it widely used in the metal manufacturing industrial training. Gu Xuejing et al.[5] developed a virtual continuous casting training platform with multiple interactive modes to enhance the training effect. Choi Ja-Yong et al.[6] developed steel-making training system, which consists of virtual machine, control panel, and initial facilities setup operation, for training skilled operators. However, these virtual casting systems only introduced the process flow, provided functions of operating equipments and setting casting parameters. Since there is few analysis on the final casting results, it is difficult for users or trainees to understand the cause and effect relationship between the process parameters and final product.

Defects have always plagued the development of the foundry industry, therefore defect prediction can help workers reasonably design or modify molds and casting parameters during HPDC. Nowadays, with the development of computer simulation technology, casting numerical simulation software, such as ProCAST®, AnyCasting® and Flow-3D® has been widely used both in research works and onsite industrial applications. Since defects reduce the overall performance of castings, and even lead to scrap castings, users[7,8] accumulate knowledge and experience of designing casting parameters to
avoid defect by using these software. These software support multiple casting processes with unified algorithms, which may not be the best solution for different types of defect prediction. Therefore, researchers\(^\text{[9,10]}\) also developed other methods to predict special defects or improve prediction accuracy.

Though numerical simulation approaches have been playing a prominent role in casting process design, existing software generally comes with comprehensive functionalities that it takes time to conduct rounds of simulation with a particular set of parameters. And certainly it may cost more time for a novice engineer to accumulate knowledge and experience. Furthermore, current solutions can only simulate the filling and solidification phases, which are only part of the overall casting process. Therefore, to bridge the gap between training and onsite applications, this work presents a neural network based defect prediction approach (DPA) for virtual HPDC. The remainder of this paper is organized as follow: Section 2 develops the neural networks based DPA. Section 3 presents the integration of DPA with virtual HPDC. And then a case study is explained in Section 4 to verify the effectiveness of proposed DPA. While the final section, Section 5 concludes the work.

2. The Neural Network based HPDC defect prediction approach

2.1. Analysis of DPA

Casting parameters that have an important effect on the control of defects, are essential factors to be considered for process planning. In HPDC, the pouring temperature (\(\degree\text{C}\)), injection pressure (MPa) and filling velocity (m/s) are the main casting parameters, and they directly affect the overall performance of casting, production efficiency and the service life of casting mold. So in this work, pouring temperature, injection pressure and filling velocity are chosen as the input data of the DPA.

In HPDC, misrun, blowholes, shrinkage and cold shut are typical defects, and hence they are the main defects need to be predicted in onsite applications. So, these defects are chosen as the prediction targets. In numerical simulation, the misrun is related to the filling rate, the blowholes and shrinkage are related to the volume of defect, and the cold shut can only be represented by 0 (not cold shut) or 1 (has cold shut), since there is no relevant criterion for better explaining it. So, the filling rate, volume of blowholes, volume of shrinkage and cold shut are the output data of DPA.

In HPDC, the relationship between casting parameters and defects is too complicated to be established by a linear model, so whether DPA can extract the nonlinear relationships is very important. Moreover, due to the multiple parameters and defects, and DPA should be real-time and universal, the finite element algorithm is too complicated and time-consuming to be used in virtual HPDC. Since neural network algorithms have the advantages of fast calculation, flexibility, and strong ability of nonlinear mapping, there are works reported on applying neural networks for data prediction\(^\text{[11-12]}\), which can fast obtain the expected result with low error rate. So this work develops a back propagation neural network (BPNN) for DPA of HPDC.

2.2. Building the BPNN

The development process of BPNN includes two parts: (a) Obtain the sample data. (b) Design the structure of BPNN. (c) Update the weight of BPNN.

1. Obtain the sample data

In order to ensure the neural network extract the nonlinear relationship between input and output, sufficient sample data is needed. For onsite applications, the numerical simulation software will be used to predicted the product result before determining the casting process plan. Therefore, ProCAST software, is adopted to obtain sample data in this work.

Firstly, the ranges of casting parameters need to be determined. Taking the motor end cover as an example, assumedly its material is ADC12 aluminium alloy, and the machine used for casting is a chamber die casting machine of horizontal layout. According to this information, the pouring temperature can be set from 560\(\degree\text{C}\) to 900\(\degree\text{C}\), the filling velocity can be set from 0m/s to 4.5m/s, and the injection pressure can be set from 0MPa to 71.7MPa.
And then, an experiment is designed to obtain as much information as possible. In this experiment, according to the range of the above casting parameters, each factor takes 7 levels, so as the combination goes, a total of 343 groups of experimental data set are designed. Then with each set of data simulate the HPDC in ProCAST accordingly, and add up the information of defects generated.

Finally, due to the different magnitude of the sample data, min-Max Normalization is adopted to map sample data to the same numerical range (0,1).

(2) Design the structure of BPNN
The structure of BPNN includes an input layer, a hidden layer, and an output layer. The input and output layers only have one layer and the number of their neurons is equal to the number of input and output parameters in the sample data. The hidden layer can be either single-layer or multi-layer, and the more the number of layers, the better the accuracy of prediction, but less efficient with the iterative calculations of the network. According to Cybenko\textsuperscript{[13]}, single-layer can make any continuous function converge, so the hidden layer is set to single-layer here to avoid complicated calculations.

The number of neurons in the hidden layer determines whether the network can meet the needs. Too few neurons will increase the prediction errors, and too much will lead to a longer learning time, and even the results cannot converge. Since there is no effective analytical formula to determine the number of neurons, so the best value can only be determine by comparing the number of iterations and mean-square error (MSE) in different numbers of neurons. According to the calculation results, the MSE of the network is the lowest when the number of neurons is 10. Therefore, the structure of the BPNN for blowholes is determined to be 3-10-4.

3. Integration of defect prediction approach with virtual HPDC
In common virtual industrial training application users can view equipments, process and environment, the real virtually, which provides clear understanding of the general process steps. While on the other hand, onsite application of HPDC utilize numerical simulation software to design process parameters and predict defects, but it lacks the visualization of the overall process. Therefore, through the integration of DPA and VR, novices can learn the HPDC process by a trial-and-error manner in the virtual environment. The virtual HPDC was realized through three modules, namely, user interface (UI), virtual environment, and DPA.

3.1. User Interface
UI is the most important feature of VR, and is also the basis for users to exchange information with the virtual scene. In the virtual HPDC, users input data and instruction through the input interface, and get information through the output interface.

The input interface is mainly used to accept process parameters input by users. The process parameters include the casting plan and casting parameters. Firstly, users need to determine the casting part type, material and die casting equipment used. Next, users can set casting parameters (Fig.1).

![Fig. 1. The casting parameters interface](image)

The output interface is used to display the casting result to users, and the casting result include the prediction data and the analysis of defects. In virtual HPDC, the prediction data is the final calculated value of the calculation module, including the filling rate, the volume of blowholes, the volume of shrinkage and the cold shut. According to the defect data and the parameters set by the user, the main reasons for the defects in the casting process are analyzed and fed back to the user.
3.2. Defect prediction approach
The calculation module is used to predict the product result by processing data and predicting defect.

(1) Data processing
The processing of casting parameters includes two parts: one is to eliminate bad data, and the other is to convert original data. Users are allowed to freely set the casting parameters within the range, so the virtual system needs to judge whether the input data is reasonable, and remind users accordingly. Since the sample data is normalized when building the BPNN, the user’s input data is also needed to be normalized, and the normalization method must be the same as before.

(2) Defect predicting
The function of defect predicting substitutes the processed data into the BPNN built in the Virtual HPDC Lab for calculation and obtain the prediction data. According to the structure and the weight of the BPNN saved in database, the calculation process (Fig.2) can be determined.

3.3. Virtual Environment
Virtual environment is the carrier of HPDC process and the support for realizing system functions. Users interact with scene model in the virtual environment through the VR display, so the development of virtual scene and display function is also needed.

First, according to the actual scene, the workshop, horizontal type chamber die casting machine and other scene models are needed to increase the immersion in virtual HPDC Lab (Fig.3). Then, adding display functions such as first-person perspective, third-person perspective and the transparent function, which makes users can observe the inner structure of the die casting machine at any time. These display functions can help novices to be familiar with the workshop and equipment.

4. Case study
In order to verify the feasibility of DPA in Virtual HPDC Lab, two experiments are designed. Firstly, an objective case study is used to test on the accuracy of defect prediction. And then, in order to study the impact of DPA on training effect and performance of the virtual system, the subjective survey is designed to test on the user experience of the Virtual HPDC Lab.

4.1. The case study on the accuracy of defect prediction
In this experiment, 10 sets of casting parameters are randomly generated in respective specified range. With these input data, two groups of results are computed, one is the simulation result obtained with the ProCAST software, so called simulation group (SG), and the other is prediction result obtained with the NN presented: experimental group (EG), are shown in the Table 3. According the comparison, the result of the numerical analysis are shown in Table 1.
4.2. Survey on user experience of Virtual HPDC Lab

In this survey, 15 people were invited to experience the Virtual HPDC Lab, and then complete the survey. The process of the survey is as follow:

Step1: Introduce the Virtual HPDC Lab.

Step2: Users conduct the HPDC experiment in the Virtual HPDC Lab without DPA.

Step3: Users conduct the HPDC experiment in the Virtual HPDC Lab with DPA.

Step4: Users carries out the numerical simulation of HPDC in ProCAST software, and the casting model, pouring material, and process parameters should be consistent with the settings in step 3.

Step5: After completing the above steps, users need to quantitatively evaluate four evaluation indicators, and each indicator is 0-10 points. The higher the score, the higher the user’s recognition of the indicator. The four indicators are:

(1) Visual immersion: Evaluate the reality of the scene in Virtual HPDC Lab.

(2) Process integrity: Evaluate the integrity of the casting process flow in the Virtual HPDC Lab with DPA by comparing with the lab without DPA.

(3) Efficiency of using DPA: Evaluate the convenience of using DPA by comparing with using the casting CAE software.

(4) System stability: Evaluate the running fluency, screen switching fluency and interaction fluency of the Virtual HPDC Lab with DPA by comparing with the lab without DPA.

Table. 2 The result of the usage questionnaire

| Number | Indicators               | Max | Min | AVE |
|--------|--------------------------|-----|-----|-----|
| 1      | Visual Immersion         | 9   | 6   | 8.00|
| 2      | Process Integrity        | 10  | 7   | 8.67|
| 3      | Efficiency of Using DPA  | 10  | 8   | 8.87|
| 4      | System Stability         | 10  | 7   | 9.00|

According to Table 2, it can been that users are generally satisfied with the Virtual HPDC Lab. The average score of indicator 4 is the highest, which shows that the number of facets of the scene model and the DPA developed in this paper does not burden the operation of Virtual HPDC Lab. In the evaluation of indicator 3, users’ score are above 8 points, which means that using DPA to predict casting result in virtual lab is more convenient than using casting CAE software. The minimum score of indicator 2 is 8, so it can be considered that the HPDC process flow is more complete and more similar to the onsite application by adding the DPA. In the average score, indicator 1 is the lowest, and its lowest score is 6. According to users’ feedback, scene models are not refined enough in material rendering and light processing, so the further optimization is needed.

According to these surveys, the Virtual HPDC Lab can provide credible data and a complete flow of HPDC process for users. So, it can be verified that the integration of DPA and VR is feasible, and can be used in enterprise training or college education.

5. Conclusion

Defect prediction can improve the production efficiency, and help novices to learn casting knowledge so as to improve their professional skills. This paper presents a BPNN based DPA, which can avoid a large number of iterative calculation, and realizes real-time prediction in VR. Through the integration of DPA and VR, the Virtual HPDC Lab can provide a complete flow of HPDC process just like in the
on site application. Through the case study on the accuracy of DPA and the survey on user experience of Virtual HPDC Lab, the effectiveness of DPA was verified, and users agree with that adding this approach makes the virtual lab more effective in training or learning.

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