Defective Casting Diagnosing Via an Enhanced Knowledge Hyper-Surface Method

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Abstract. The research on the analysis of cause and effect relationships in castings has always been a centre of attention in the manufacturing industry. An intelligent diagnosis system should be able to diagnose effectively the causal representation and also justify its diagnosis. Recently, a method, known as the Knowledge Hyper-surface method which used Lagrange Interpolation polynomials has gained more popularity in learning cause and effect analysis in casting processes. The current method show that the belief value of the occurrence of cause with respect to the change in the belief value in the occurrence of effect can be modelled by linear, quadratic or cubic relationships and the method retained the advantages of neural networks and overcomes their limitations in learning the input-output mapping function in the presence of noisy, limited and sparse data. However, the methodology was unable to model exponential increase/decrease in belief values in cause and effect relationships. This paper proposed an enhancement to the current Knowledge Hyper-surface method by introducing midpoints in the existing shape formulation which further constrains the shape of the Knowledge hyper-surfaces to model an exponential rise in belief values but without exposing the dataset to the limitations of 'over fitting'. The ability of the proposed method to capture the exponential change in the belief variation of the cause when the belief in the effect is at its minimum is compared to the current method on real casting data.

Introduction

Every day foundries manufacture a large number of castings. Every time a casting is produced, a large amount of data is generated involving process-parameter values and one or more indicators on whether the casting is defective or not. This data is encoded for each type of defect, for each day, week and month of the casting process and is available for all casting components.

The rejection data for a given casting and time frame, normally indicates a pattern, which has normally few defects occurring at significantly high proportions and some occurring at significantly low proportions. Therefore, the diagnostic casting problem was defined as recognising patterns in the casting rejection data and identifying a corresponding combination of causes. It was observed that a combination of defects generally occurs as a result of a combination of causes [1].

The cause and effect relationship in a casting process is complex and non-linear. Furthermore, a large number of parameters are needed to be coordinated with each other in an optimal way to minimise the occurrence of defective castings. This has led to the necessity of developing computer-based optimisation techniques. An optimisation process is a computational technique that determines an optimal value for process parameters such that the magnitude of one or more response variables of the process is minimised. It also ensures that the process operates within established limits or constraints [2]. Casting process optimisation has facilitated foundry men in making right choices, but it still remains a challenging area that has drawn the attention of many researchers during the last two decades.

Recent studies have used the response surface method (RSM) to optimise parameters in the casting of process parameters increase [4]. This is mainly because RSM techniques show the same limitations as showed by polynomial-regression techniques; the number of unknowns in the system increases exponentially with the number of parameters.

In contrast, Taguchi's robust design method provides a process engineer with a systematic and efficient approach for conducting experimentation to determine near optimum settings of design parameters for performance and cost [5]. The robust design method uses orthogonal arrays (OA) to study the parameter space, usually containing a large number of decision parameters, with a small number of experiments. To this date, a quite significant amount of research and development work has been done in order to optimize parameters of the casting process by using the Taguchi method [6].

Recently, the artificial-neural networks (ANN), or simply neural-networks (NN), technique has gained more popularity in learning cause and effect analysis in casting processes [7]. ANN consists of interconnected cells, called neurons, and simulates the behaviour of the biological neural network in a human brain [8]. Neural-networks' techniques are able to adapt, learn from examples and are generally used to model complex relationships between inputs and outputs or to classify data finding common patterns [9]. This ability makes the field of diagnosis a potential application for neural networks.

Ransing [1] proposed a method that retains advantages of regression analysis and neural-network techniques and at the same time overcomes the limitations of both techniques. The Knowledge Hyper-surface method described that the belief variation in the occurrence of a cause, with respect to a change in the belief value of the occurrence of an effect, follows a pattern. Such a variation is generally linear, quadratic or cubic and certainly not an arbitrary higher-ordered polynomial.

Despite the superior extrapolation abilities of the current knowledge Hyper-surface method, two major limitations have been identified: (a) the use of higher ordered polynomials can lead to the 'over-fitting' effect as observed in other interpolation techniques including neural networks, (b) An exponential rise in the belief value cannot be modelled by lower-ordered polynomials such as quadratic and cubic Lagrange interpolation polynomials.

This paper proposed an enhancement to the current Knowledge Hyper-surface method by introduces midpoints in the existing shape-function formulation so that an exponential rise in the belief-value variation can be modelled without introducing the effects of 'over fitting'.

The remaining of the paper is organized as follows: Section two illustrates the proposed method which enhanced the current knowledge hyper-surface method. In Section three, the abilities of the proposed method to capture the exponential change in the belief variation of the cause when the belief in the effect is at its minimum is compared with the outputs from the current method on a real casting data set. The paper is concluded in the final section along with short discussion on further research.

The Proposed Enhancement

In this section, a detail description of the proposed enhancement on the current Knowledge Hyper-surface method proposed by Ransing [1] is given. The proposed enhancements are implemented in the method to overcome the limitations by constructing midpoints between each primary weight along each dimension. The new improved algorithm is then tested on real casting data in the next section.

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The method described that to model an n^{th} order relationship along a dimension, $(n+1)$ equidistant reference points between -1 and +1 are chosen. For each reference point 'i' $(i=1$ to $n+1)$, a one-dimensional Lagrange Interpolation Polynomial is used based on the following formula:

$$=\frac{\xi-\xi_0}{\xi_k-\xi_0}*\frac{\xi-\xi_1}{\xi_k-\xi_1}*\frac{\xi-\xi_2}{\xi_k-\xi_2}*\dots*\frac{\xi-\xi_{k-1}}{\xi_k-\xi_{k-1}}*\frac{\xi-\xi_{k+1}}{\xi_k-\xi_{k+1}}*\dots\frac{\xi-\xi_n}{\xi_k-\xi_n} \quad (1)$$

where:

n : Order of the Lagrange Interpolation Polynomial (e.g. one for linear; two for quadratic; three for cubic; etc.)

k : A reference point at which the one-dimensional Lagrange Interpolation Polynomial $l_k^n(\xi)$ is constructed (k ranges from 0 to n).

i : Ranges from one to total number of reference points, i.e. $(n+1)$.

The variable ξ is used to store the belief value representing the strength of the corresponding effects, ranges from -1 to +1. For one-dimensional Lagrange Polynomial Interpolation the reference points are drawn along this dimension. Whereas for a given cause connected to 'p'effects, the Lagrange Interpolation Polynomial at a reference point 'i' is defined as 'p' dimensional and is given by the following equation:

$$l_i(\xi^1,\xi^2,\xi^3,\dots,\xi^j,\dots,\xi^p)=l_{k_1}^{n_1}(\xi^1)*l_{k_2}^{n_2}(\xi^2)*\dots*l_{k_j}^{n_j}(\xi^j)*\dots l_{k_p}^{n_p}(\xi^p) \quad (2)$$

where:

$$l_{k_j}^{n_j}(\xi^j)=\frac{\xi^j-\xi_0^j}{\xi_{k_j}^j-\xi_0^j}*\frac{\xi^j-\xi_1^j}{\xi_{k_j}^j-\xi_1^j}*\dots*\frac{\xi^j-\xi_{k_j-1}^j}{\xi_{k_j}^j-\xi_{k_j-1}^j}*\frac{\xi^j-\xi_{k_j+1}^j}{\xi_{k_j}^j-\xi_{k_j+1}^j}*\dots\frac{\xi^j-\xi_{n_j}^j}{\xi_{k_j}^j-\xi_{n_j}^j} \quad (3)$$

n_j : The order of one dimensional Lagrange Interpolation Polynomial $(l_{k_j}^{n_k}(\xi^j))$ corresponding to j^{th} dimension that represents the relationship between j^{th} effect and the cause under consideration.

k_j : Reference point along j^{th} dimension, at which the one-dimensional Lagrange Interpolation Polynomial $l_{k_j}^{n_k}(\xi^j)$ is evaluated. (k_j Independently ranges from 0 to n_j for each Lagrange Polynomial Interpolation).

$\xi_0^j,\xi_1^j,\xi_2^j,\dots,\xi_{n_j}^j$ are (n_j+1) reference points along the j^{th} dimension.

i : for a 'p' dimensional case, 'i' ranges from one to the total number of reference points 'q' as given below:

$$q=(n_1+1)*(n_2+1)*(n_3+1)*\dots*(n_j+1)*\dots*(n_p+1) \quad (4)$$

The method also prescribed that a Lagrange Interpolation polynomial and a weight value can be associated with each of the said reference points as shown by the equation below:

$$\text{The belief value in the cause}=\sum_{i=1}^{q}w_i l_i(\xi^1,\xi^2,\dots,\xi^p) \quad (5)$$

where:

q : Total number of reference points.

$l_i(\xi^1,\xi^2,\dots,\xi^p)$ is given by Equation 1

w_i : Weight variable associated with the i^{th} reference point.

By considering a weight value at a reference point to be representative of the belief value in the cause, the total number of weights is therefore the same as the total number of reference points. However, as the number of dimensions increased, the total number of weights in a network also increased exponentially. This rapidly increased the number of unknown variables within the network and it was not a practical implementation, as it would not only slow down the system, but also requires an excessively large training dataset.

In order to overcome that limitation, this research proposed an enhancement by dividing the reference points into two categories, referred to as primary and secondary reference points. Weight values associated with these primary reference points have been considered as independent variables (primary weight values) and other weight values associated with secondary reference points (secondary weight values), have been considered to be linearly dependent on one or more primary weight values.

For a ' p ' dimensional problem, the total number of primary weights is calculated as:

$$\text{Primary weights} = \left[\left(\sum_{j=1}^{p} n_j + 1\right) - (p-1)\right] \tag{6}$$

As a result, all weights associated with primary reference points 1, 2, 3, 4 and 7 are primary weights. The secondary weight values at locations 5, 6, 8 and 9 are expressed as a linear combination of the primary weights and in particular:

$$w_5 = \frac{c(w_2 + w_4)}{2} \tag{7}$$

$$w_6 = \frac{c(w_3 + w_4)}{2} \tag{8}$$

$$w_8 = \frac{c(w_2 + w_7)}{2} \tag{9}$$

$$w_9 = \frac{c(w_3 + w_7)}{2} \tag{10}$$

Results and Discussions

The abilities of the proposed algorithm to capture the exponential change in the belief variation of the cause when the belief in the effect is at its minimum is compared with the outputs from both the current method on a real casting data set used by Ransing [1]. The data was collected from 'Kaye Preistigne'– a pressure die casting foundry. A total of 14 defects were identified and associated with 43 process, material or design parameters. The data was collected for similar components over a period of one year. A total of 60 representative examples were finalised.

A belief value in the occurrence of defects was calculated as corresponding to the belief values representing the occurrence and non-occurrence of associated process, design and material parameters as given by the experts in the foundry. Three defects known as 'Porosity', 'Mismakes' and 'Dimensional' are identified.

For the purpose of comparison, the graphical variation of belief surfaces learnt by the conventional neural network, Ransing [1] and the proposed method is showed only on two defects which are 'Porosity' and 'Mismakes'.

Figures 1 and 2 shows the variation in the belief values in the occurrence of "The position of gate" for belief values for defects "Porosity" and "Mismakes" using the proposed method and Ransing's method. It can be easily observed the proposed method has an ability to accurately model the exponential rise in the belief values than the other two techniques.

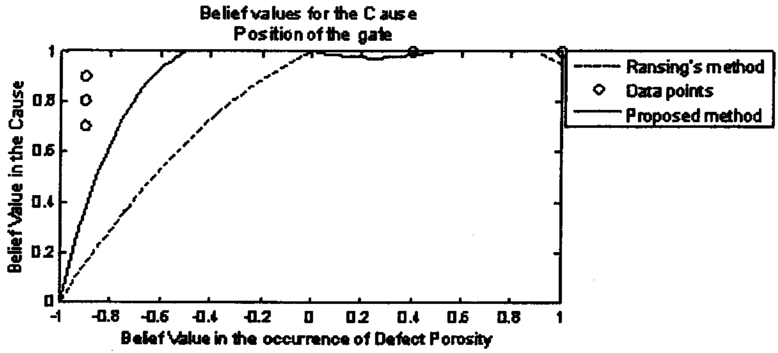

Fig.1: The performance of Ransing's method and the proposed method for 1-Dnal belief value variation modeled by Quadratic Network for defect Porosity.

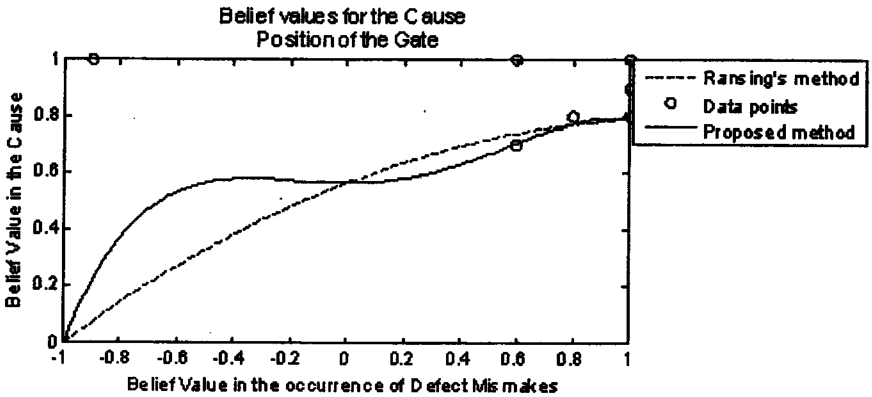

Fig.2: The performance of Ransing's method and the proposed method for two dimensional Quadratic network for defect Mismakes.

Summary

An enhancement to the current Knowledge Hyper-surface method has been proposed in this paper. The method introduces mid points in the existing shape function formulation so that an exponential rise in the belief value variation can be modelled without introducing the effects of 'over fitting'. The performance of the proposed method was compared with the current method proposed by Ransing[1] on the same casting data used by Ransing [1]. The results clearly demonstrated that the proposed method does not have limitations as been identified by the current method. Furthermore, with the result of this research achievement, it will now be possible to correctly predict the sensitivity of process parameter variations to the occurrence of defects. This is an important area of research in a robust design methodology.

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