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Enhancing Knowledge Hyper Surface Method for Casting Diagnosing

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ABSTRACT

The diagnosis of defective castings has always been a centre of attention in the manufacturing industry. This is mainly because 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. An intelligent diagnosis system is needed to diagnose effectively the causal representation and also justify its diagnosis. A previous 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 modeled 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.

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1. 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 is generally complex and highly interlinked for many manufacturing processes. Identification of the degree of influence of a cause on the occurrence of a defect is one of the most difficult tasks in a diagnostic process and the highly interlinked causal relationship further complicates the problem. 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 process [3], [4]. The computational efficiency of the RSM approach significantly reduces as the number of process parameters increase [5]. 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 [6], [7], [8]. 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 optimise parameters of the casting process by using the Taguchi method [9], [10], [11], [12].

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 [13], [14], [15], [16], [17], [18]. ANN consists of interconnected cells, called neurons, and simulates the behaviour of the biological neural network in a human brain [19]. 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 [20]. This ability makes the field of diagnosis a potential application for neural networks.

A new approach, which is of direct relevance to the manufacturing industry, was proposed by Ransing [1]. The proposed method used Lagrange Interpolation polynomials to explore how the degree of influence of each cause on the occurrence of a defect or a combination of defects can be quantified based on past diagnostic examples. For some selected data sets the method showed superior extrapolation abilities as a result of the networks' ability to constrain the shape of the resulting multi-dimensional hyper-surface to the known variation in the belief values in causes and effects. Furthermore, the proposed method had reduced the number of unknowns to an acceptable number which improved computational efficiency as compared to the RSM approach.

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 modeled 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 introducing midpoints in the existing shape-function formulation so that an exponential rise in the belief-value variation can be modeled without introducing the effects of 'over fitting' to the dataset.

The remaining of the paper is organized as follows: Section 2 presents the the overview of the current method which discusses the implementation of Lagrange Interpolation Polynomials into the current Knowledge hyper-surface method and highlights the advantages and limitations of the current method in learning from examples. The enhancements and mathematical solution of the proposed method is presented in Section 3. The performance of the proposed method is further illustrated in Section 4 by comparing its solution with the previous version of the Knowledge hyper-surface method on real casting data. Finally, the conclusions are drawn from the research presented in this chapter

2. OVERVIEW OF THE CURRENT KNOWLEDGE HYPER SURFACE METHOD

In previous research, Ransing [1] proposed a method known as The Knowledge Hyper surface Method that retains advantages of regression analysis and neural network techniques and at the same time overcome 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.

The method described that to model a 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:

$$l_i(\xi) = l_k^n(\xi) = \frac{\xi - \xi_0}{\xi_k - \xi_0} * \frac{\xi - \xi_1}{\xi_k - \xi_1} * \frac{\xi - \xi_2}{\xi_k - \xi_2} * \ldots * \frac{\xi - \xi_{k-1}}{\xi_k - \xi_{k-1}} * \frac{\xi - \xi_{k+1}}{\xi_k - \xi_{k+1}} * \ldots \frac{\xi - \xi_n}{\xi_k - \xi_n} \quad (1)$$

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:

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

where,

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

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).

$\xi_0^j, \xi_1^j, \xi_2^j, \ldots, \xi_{n_j}^j$ 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.

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

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

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

Where,

q : Total number of reference points.

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

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 are therefore the same as the total number of reference points. However, this formulation had its own limitation. 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 require an excessively large training data set.

In order to overcome that limitation, Ransing [1] then divided 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 (see Figure 1).

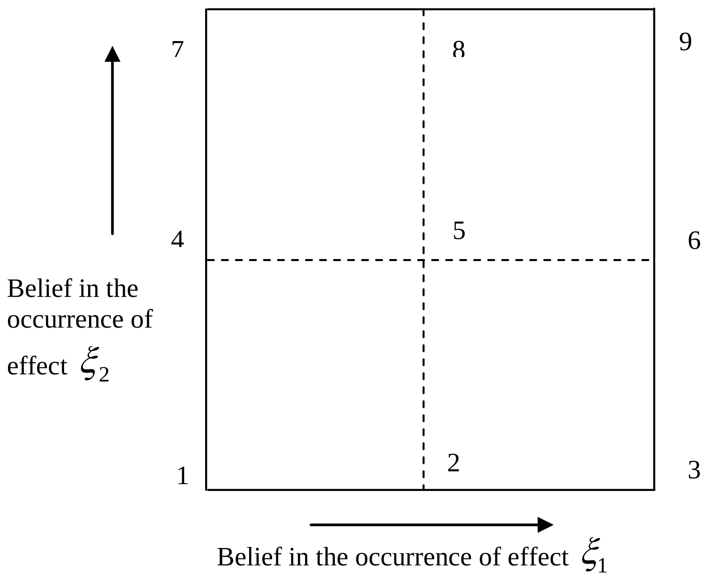

Figure 1. Dependent (1, 2, 3, 4, 7) and Independent Weight Values (5, 6, 8, 9) that associated with Reference Points 1 to 9.

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 we can see from Figure 1, 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:

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

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

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

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

2.1. Advantages of the Current Knowledge Hyper Surface Method

Two major advantages of the current Knowledge Hyper Surface Method have been discovered:

(a) The current method was capable to a-priori storing any known information about the cause-effect relationship within the network and at the same time was able to learn from examples. For some selected data sets the proposed algorithm has shown superior extrapolation abilities as compared to the multi layer neural network. The extrapolation ability was enhanced by the networks ability to constrain the shape of the resulting multi-dimensional hyper-surface to the known variation in the belief values in causes and effects.

(b) The dependence of the secondary weight values on the primary weight values had reduced the number of unknowns to an acceptable number.

2.2. Limitations of the Current Knowledge Hyper Surface Method

Despite the superior extrapolation abilities of the current knowledge hyper surface method, two major limitations have been identified.

(a) 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 (as shown in Figure 3) cannot be modelled by lower ordered polynomial such as quadratic and cubic Lagrange interpolation polynomials.

To demonstrate the over fitting effect, the following data set is created by choosing a few data points and then a maximum of twenty percent noise with normal distribution with mean zero and unit standard deviation value is added randomly. The variations are plotted using linear, quadratic and quartic shape functions to observe the performance of the current method as shown in Figure 2.

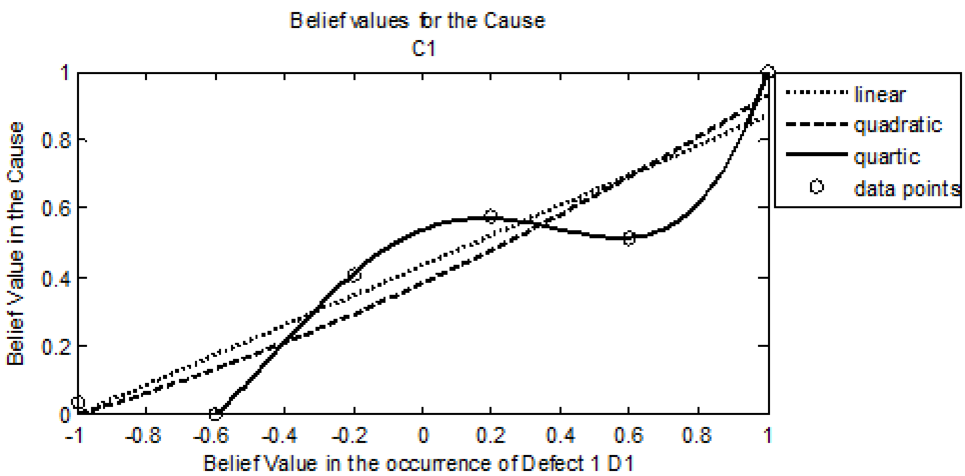

Figure 2. Clearly shows that the use of quartic shape functions in the current knowledge hyper-surface method had fit all the data points perfectly as compared to others but the resulting shape of the decision hyper-surface is unrealistic and is a clear case of ‘over fitting’ to the data points.

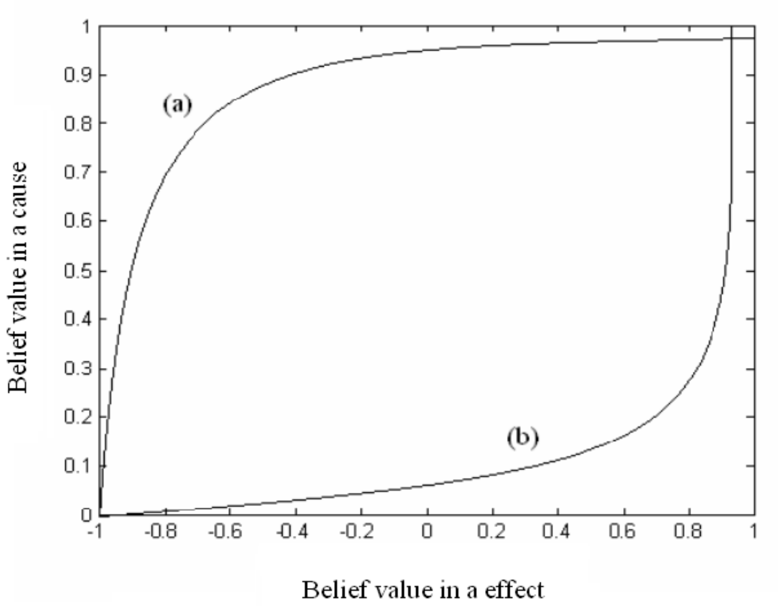

Figure 3. Exponential increase in the belief value of a cause

The performance of the current knowledge hyper-surface method is assessed on data points generated from curves (a) and (b) in Figure 3 and is shown in Figure 4 and Figure 5 respectively. It is clear that lower ordered polynomial can not model the exponential rise in belief values where in the higher ordered polynomials tend to overfit the data points.

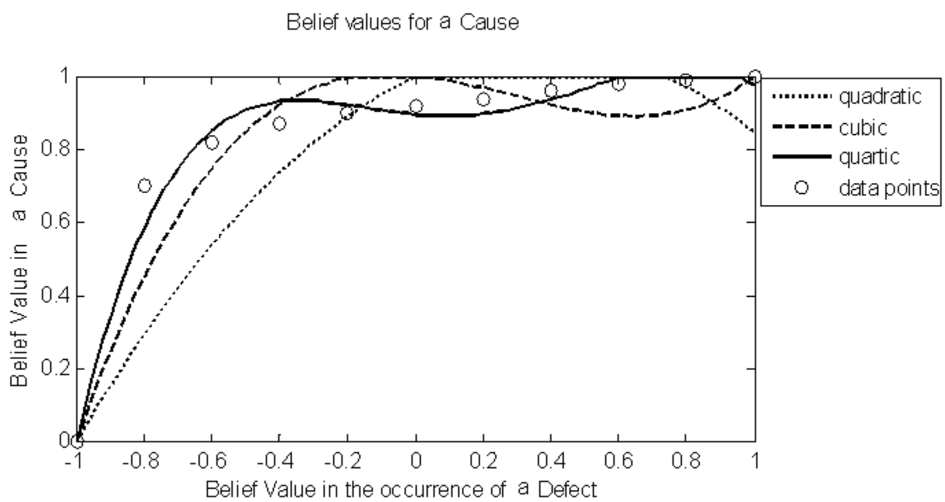

Figure 4. Belief value variation modelled by quadratic, cubic and quartic polynomials on a set of data points as shown.

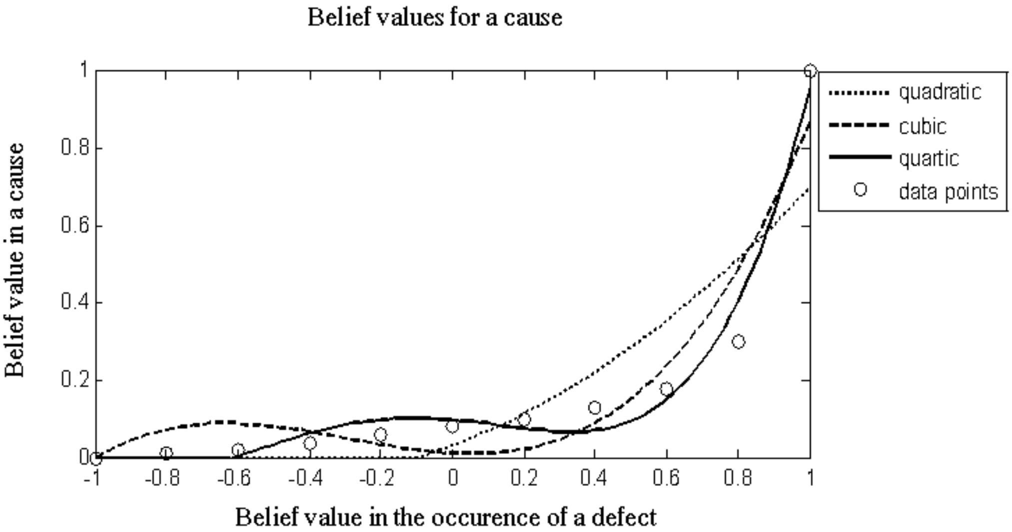

Figure 5. Belief value variation modelled by quadratic, cubic and quartic polynomials on a set of data points as shown.

The following section will discuss the modification that has been proposed to overcome the above mentioned limitations within the existing technique.

3. ENHANCEMENTS TO THE CURRENT KNOWLEDGE HYPER SURFACE METHOD

In the current Knowledge hyper-surface method, the multi-dimensional hyper surface is constructed from one dimensional belief curves. Once the shape of each one dimensional curve is determined, the shape of the hyper surface gets automatically determined. Hence the challenge for the proposed enhancement is to be able to model the exponential rise by higher ordered polynomials without introducing the side effects of over fitting the possible noise in data points.

This is achieved by a two stage optimisation process. As can be seen in Figure 6, first the belief values at the end of points and the mid point are determined using a quadratic Lagrange interpolation polynomial and employing the current knowledge hyper-surface method. This method determines the primary weight values at the end and mid reference points. The exponential rise is either in the first half of the belief curve or in the second half.

This effect is modelled by introducing a further reference point between the end and mid reference point. The primary weights determined previously at end and mid reference points are kept constant and optimal values for the two new reference points (x_1 and x_2) are determined by a second stage optimisation process using the current knowledge hyper method using 4th ordered (quartic) Lagrange interpolation polynomials.

The primary weight values at the two new reference values are constrained such at that they lie between the corresponding primary weight values at the neighbouring end and mid reference point as shown in Figure 6.

In the proposed new method, midpoints are constructed between each primary weight along each dimension such that

1. 0 (i.e. origin at point 1) <= x1<= primary_weight at point 2, and
2. primary_weight at point 2 <= x_2<= primary_weight at point 3.

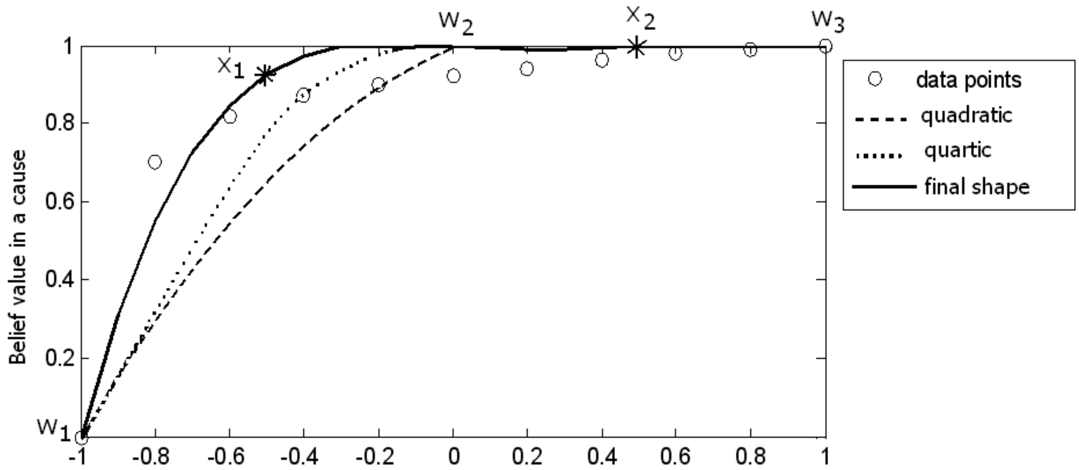

Figure 6. Shape of the resulting curve after a two stage of optimisation process. It ensures that X_1 is between W_1 and W_2 and X_2 between W_2 and W_3 .

4. THE PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH THE CURRENT METHOD ON REAL CASTING DATA SETS

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 both the current Knowledge hyper-surface method and a multi layer neural network on a real data set. This data set was also 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. For this case study as shown in Table 5.4, 16 process parameters, 3 defects and 11 examples were chosen. The same information was also used by Ransing [1].

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 and all defects chosen are represented as defect A, defect B and defect C as shown in Table 1.

For the purpose of comparison, the graphical variation of belief surfaces learnt, the current method and the proposed method is showed only on two defects which are 'Porosity' and 'Mismakes'. The belief values which were used in a training data set are shown in Table 1.

Table 1. The training dataset with target output values for the input defects

Defects: Strength of Defects:		Defect A		Defect B		Defect C		
		1		0		0		
		1		0		0		
		1		1		0		
		0.7		1		0		
		1		0.8		0		
		0.7		1		0		
		0		1		0		
		0		1		0		
		0		1		0		
		0		0.8		1		
		0		0.9		1		
Output node Numbers: Target Output Values:	1	2	3	4	5	6	7	8
	0.8	0	0	0	1	1	1	1
	0.8	0	0	0	1	1	1	1
	0.8	0.7	0	0	1	1	1	1
	0.8	0.7	0	0	1	1	1	1
	0.8	0.7	0	0	1	1	1	1
	0.8	0.7	0	0	1	1	1	1
	0	0	0	0	0	0	0	0.8
	0	0	0	0	0	0	0	0.8
	0	0	0	0	0	0	0	0.9
	0	0.7	1	0.7	0	0	0	0.7
	0	0.8	1	0.7	0	0	0	0.8
Output Node Numbers: Target Output Values:	9	10	11	12	13	14	15	16
	1	0.9	1	0.8	0	0	0	0.9
	1	0.9	1	0.8	0	0	0	0.9
	1	1	1	0.8	0.8	0.7	0	0.9
	1	1	1	0.8	0.8	0.7	0	0.8
	1	1	1	0.8	0.8	0.7	0	0.9
	1	1	1	0.8	0.8	0.7	0	0.8
	0	0.9	0.7	0	0.7	0	0	0
	0	0.9	0.7	0	0.7	0	0	0
	0	0.9	0.7	0	0.8	0	0	0
	0	0.9	0	0.7	0.7	0	0	0
	0	1	0.7	0.7	0.7	0	0	0

A quadratic variation between input and output relationships was assumed in both the current method and the proposed method. Both networks were trained on the training dataset as shown in Table 1. Codes for all methods have been written in MATLAB.

All networks achieved the target error of 0.001 and seemed to have learnt the training dataset. The speed of all networks in learning the training dataset is not the main concern in this test, as the resulting shape of the hyper surface is of importance. The belief surface has been plotted for cause ‘The position of gate’ (cause number 8) which influences the occurrence of ‘Porosity’ (defect A) and ‘Mismakes’ (defect B) as this data requires to model the exponential rise in the belief values variation.

5. RESULT AND DISCUSSION

The variation in the belief value in the occurrence of ‘The position of gate’ for defect A, i.e. ‘Porosity’ using the current method and the proposed method is plotted when only defect A is connected to the cause (one-dimensional case) and when both defects (i.e. defects A and B) are connected to the cause (two-dimensional case). The results are shown in Figures 7 and Figure 8. Since the proposed method is able to model an exponential increase in belief values, it was shown to be a better fit to data points using the quadratic polynomials as compared to the current method. This is because of the introduction of midpoints which gives an additional degree of freedom to control the resulting curve. However, as demonstrated by Ransing [1] neural networks do not guarantee a better shape for hyper surfaces. Neural networks tend to interpolate better point and exhibit all the limitations as identified by Ransing [1].

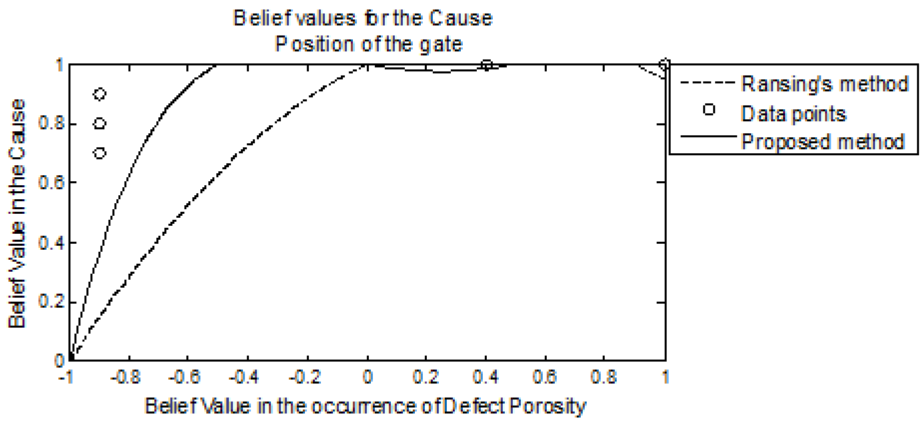

Figure 7. The performance of Ransing's method and the proposed method for one-dimensional belief-value variation modelled by quadratic polynomials for defect Porosity.

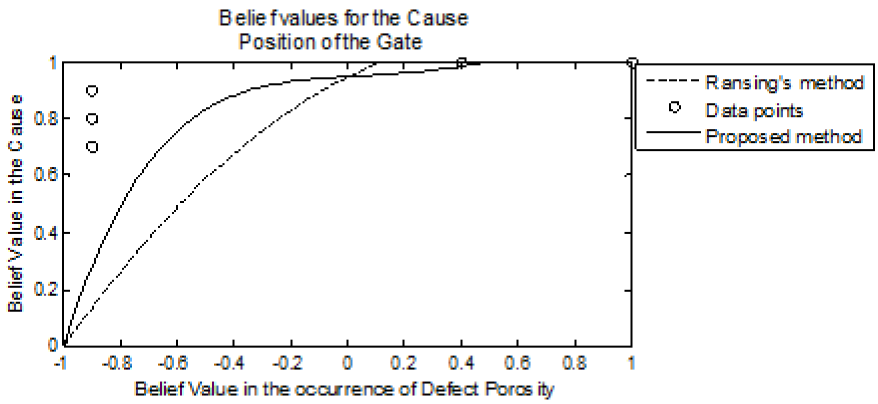

Figure 8. The performance of Ransing's method and the proposed method for 2D belief-value variation modelled by quadratic polynomials for defect Porosity.

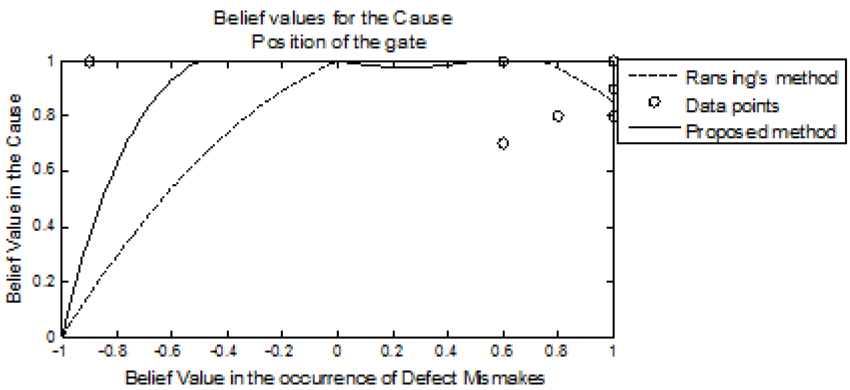

Figure 9. The performance of Ransing's method and the proposed method for 1D belief variation modelled by quadratic polynomials for defect Mismakes.

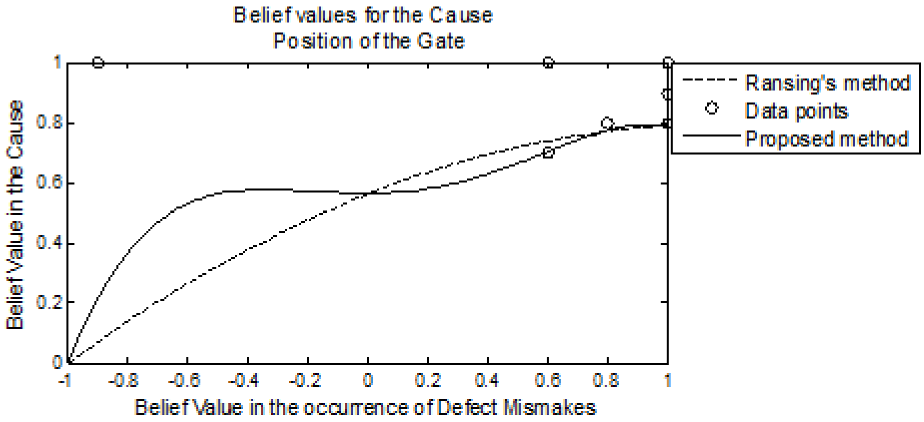

Figure 10. The performance of Ransing's method and the proposed method for 2D belief variation modelled by quadratic polynomials for defect Mismakes.

The simulation results in Figure 9 and Figure 10 clearly demonstrate that the proposed method outperform the performance of the current method in getting a better fit to data points. The introduction of midpoints by the proposed method gives an additional degree of freedom in controlling the resulting curve. Furthermore, the proposed method is able to model an exponential increase in belief values by showing a better fit to data points using the quadratic polynomials as compared to the current method.

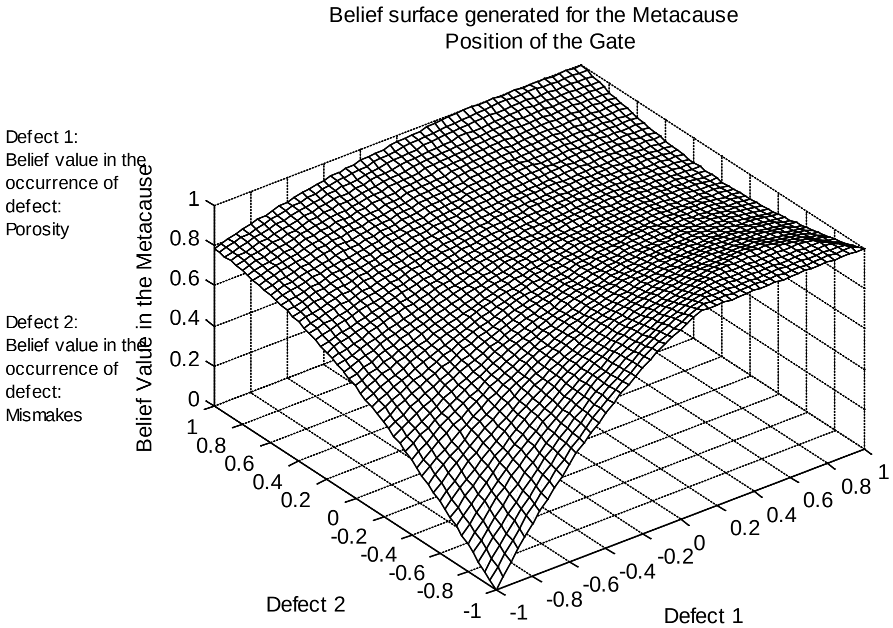

Figure 11. Two Dimensional quadratic output surface for defects Porosity and Mismakes generated by Ransing's method.

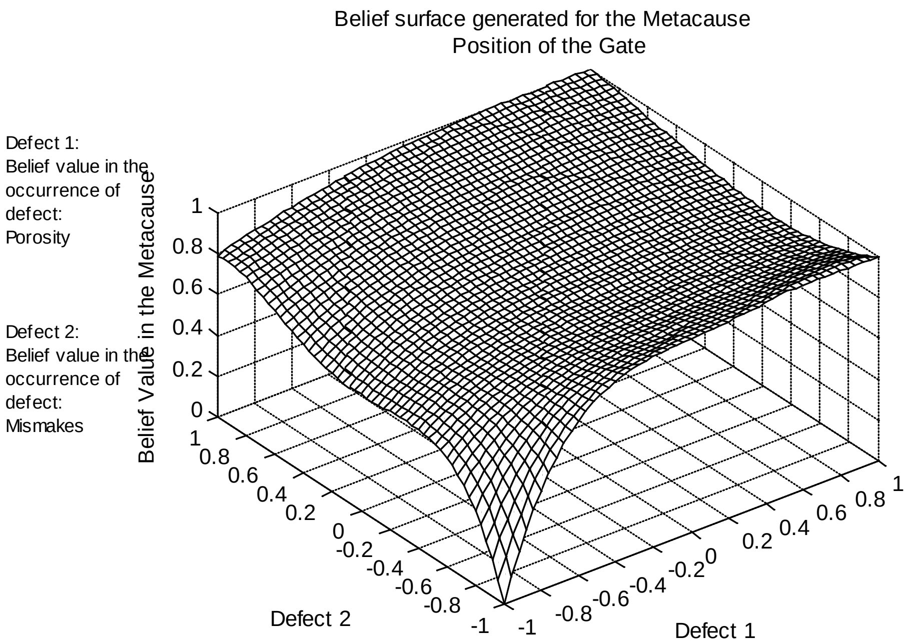

Figure 12. Two Dimensional quadratic output surface for defects Porosity and Mismakes generated by the proposed method.

Figures 11 and Figure 12 show 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, Ransing's method and the neural-network method. It can easily be observed that the proposed method has an ability to accurately model the exponential rise in the belief values rather than the other two techniques.

6. CONCLUSION

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 modeled 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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