Process Parameter Optimization via Data Mining Technique

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Abstract: - Data mining can be viewed as a power tool or technique to help process engineers understand their process know-how. The potential intelligence behind manufacturing processes should hold the information about process improvement or product development. Namely, mining such manufacturing intelligence will have positive contributions to aid the competition capability of enterprise. In this study, we proposed a data mining technique based on artificial neural networks (ANNs) to mine the manufacturing intelligence for achieving the issue of parameter optimization. The rationality and feasibility of the proposed procedure can also be demonstrated well according to the illustrative example in this study.

Key-Words: - manufacturing intelligence (MI), data mining, parameter optimization

1 Introduction

To survive during the competitive business environment, the lower cost, higher quality and rapidly response are always the focuses mentioned by most enterprises. The primary reason is that the better quality can reduce the unnecessary cost (e.g. the problem of rework) and the time-to-market can also be shortened at the same time. Basically, optimizing the product or process design in support of on-line quality control, off-line quality control is a cost-effective method. In off-line quality control, the product or process quality is the response that the manufacturers focus on. The response of a product or the response of an operational process will be heavily influenced by the control factors and noise factors. The control factors are those factors which the designer can control, and the noise factors are those factors which the designer can not control or too expensive to control [7, 14, 16, 17]. For manufacturers, finding out the robust process parameters or robust operational parameters will be an important objective. The robust process parameters or robust operational parameters are desired to obtain the process parameter settings for a product or an operational process in such a manner that the product response attains its desired target with minimum variation [16, 17].

For manufacturing industries, each manufacturing process will hide the potential domain knowledge. If we can sufficiently include the professional knowledge and engineering experience into the product design and production, it will shorten the time to development, ensure the quality of product and enhance the competitive capability [10, 11, 20]. Under the trend of knowledge economy, most enterprises pay much attention to the issue of knowledge management to enhance their core competitions. Data mining (i.e. data or knowledge discovery) can be viewed as a process of analyzing data from different perspectives and summarizing it into useful information [1, 4, 5, 6, 19]. Data mining will help us optimize our business decisions, increase the value of each customer and communication, and improve satisfaction of customer with the necessary services. That is, data mining can help us reveal knowledge hidden in data and turn this knowledge into a crucial competitive advantage. Artificial neural networks (ANNs) have been used in a wide variety of applications, ranging from classification and pattern recognition to optimization and control [8, 9, 13, 15]. Hence, in this study, we will propose a procedure based on the ANNs data mining technique to address the issue of mining BI to achieve parameter optimization.

2 Literature Review

2.1 Data Mining

Generally, data mining (i.e. data or knowledge discovery) can be viewed as a process of analyzing data from different perspectives and summarizing it into useful information [1, 4, 5, 6, 19]. The obtained information can be then used to increase revenue, cuts costs or both. The importance of collecting data that reflect your business or scientific activities to achieve competitive advantage is widely recognized now. However, the bottleneck of turning this data into your success is the difficulty of extracting knowledge from the collected data. Data might be one of the most valuable assets for corporation. However, the important thing is that we must know how to reveal valuable knowledge hidden in raw data. Data mining allows us to extract diamonds of knowledge from our historical data and predict outcomes of future situations. It will help us optimize our business decisions, increase the value of each customer and communication, and improve satisfaction of customer with the necessary services. Data that require analysis differ for companies in different industries. That is, data mining can help us reveal knowledge hidden in data and turn this knowledge into a crucial competitive advantage.

The capabilities of using Data mining can be summarized as follows:

1. Identify the best prospects and then retain them as customers.
2. Predict cross-sell opportunities and make recommendations.
3. Learn parameters influencing trends in sales and margins.
4. Segment markets and personalize communications.

Several types of analysis are available [2], e.g. the Artificial neural networks (Non-linear predictive models that learn through training and resemble biological neural networks in structure); Genetic algorithms (Optimization techniques that use processes such as genetic combination, mutation, and natural selection in a design based on the concepts of natural evolution); Decision trees (Tree-shaped structures that represent sets of decisions. These decisions generate rules for the classification of a dataset); Nearest neighbor method (A technique that classifies each record in a dataset based on a combination of the classes of the k record(s) most similar to it in a historical dataset (where k 1). Sometimes called the k-nearest neighbor technique); Rule induction (The extraction of useful if-then rules from data based on statistical significance); Data visualization (The visual interpretation of complex relationships in multidimensional data. Graphics tools are used to illustrate data relationships).

2.2 Self-Organizaing Mapping Neural Network (SOMNN)

The architecture form of the SOMNN network is based on the understanding that the representation of data features might assume the form of a self-organizing feature map that is geometrically organized as a grid or lattice. In the pure form, the SOMNN defines an "elastic net" of points (parameter, reference, or codebook vectors) that are fitted to the input data space to approximate its density function in an ordered way. The algorithm takes thus a set of N-dimensional objects as input and maps them onto nodes of a two-dimensional grid, resulting an orderly feature map [12, 18].

The components in SOMNN are the input layer and the topological map, a layer of nodes topologically structured. Two-dimensional array of output nodes was used to form self-organizing map. Every input node is connected to every output node via a variable connection weight. A layer of two-dimensional array of competitive output nodes is used to form the feature map. The lattice type of array can be defined to be square, rectangular, hexagonal, or even irregular. The most used forms are the square and the hexagonal arrays of nodes. This structure is not explicitly defined in the architecture of the network at the moment of its design. The interest of this network resides in the neighborhood structure that develops progressively by learning and arises from the nodes behavior. It is the self-organizing property. The SOMNN belongs to the category of the unsupervised competitive learning networks [12, 15, 18]. It is called competitive learning because there is a set of nodes that compete with one another to become active. In the SOMNN, the competitive learning means also that a number of nodes is comparing the same input data with their internal parameters, and the node with the best match (or it can be said as winner) is then tuning itself to that input, in addition the best matching node activates its topographical neighbors in the network to take part in tuning to the same input. More a node is distant from the winning node the learning is weaker. It is also called unsupervised learning because no information concerning the correct clusters is provided to the network during its training. Like any unsupervised clustering method, the SOMNN can be used to find clusters in the input data, and to identify an unknown data vector with one of the clusters. Moreover, the SOMNN represents the results of its clustering process in an ordered two-dimensional space (R2). A mapping from a high dimensional data space Rn onto a two dimensional lattice of nodes is thus defined. Such a mapping can effectively be used to visualize metric ordering relations of input data.

3 Proposed Procedure

The technique of clustering analysis will be a suitable tool and be chosen in this study. The primary reason is: “There are many historical manufacturing data be stored or recorded for most enterprises, and the partial data will denote the similarity features in the real application. Hence, we can group those historical data according to those attributes to mine the available business intelligence or the business intelligence." Artificial neural networks (ANNs) had been employed to achieve the modeling, prediction, classification and clustering analysis [10, 15, 20]. Basically, two kinds of learning model for ANNs are mentioned: one is the supervised model and the other is unsupervised model. As for the problem of clustering analysis, the unsupervised learning model will be frequently used to most applications [12, 15, 18]. The SOMNN is the popular one among those models up to now. Hence, we will apply SOMNN into our clustering analysis in this study. The detailed steps will be also given as follows:

<u>Step 1. Inputting the requirements.</u>

Firstly, the engineers can initially collect the requirements information for the particular products. Such information will include the basic attributes of the manufactured products and the expected qualities for the particular responses, they can be denoted as (attribute1, attribute2,…, repsonse1, response 2,…).

<u>Step 2. Making judgment.</u>

The clustering analysis will be necessary activities before performing the expert system. Herein, SOMNN is applied to our clustering analysis. The detailed operations of SOMNN can be referred to [12, 18]. The input items for performing the clustering analysis are (attribute1, attribute2,…, repsonse1, response 2,…) according to the manufactured products and processes. The item with the similar characteristics will be grouped into the same cluster. Due to the requirement of decision-making, we also designed an index RS and RF which will be the ratio for the particular level setting of the parameter in the success cases and the ratio for that in the failure data set, to compare with the pre-defined cutoff values. Two cutoff values are set by the engineers: one is the maximum value (Mc) and the other is the minimum value (mc). The larger Mc value will reduce the opportunities for the parameters' level being chosen and the less mc value will lead to the difficult and complicated decision-making. Hence, the practitioners can decide them according to their real situation. The relationship among RS, RF, Mc and mc will be given as Table 1. Where the term of (Para_S – Para_F) will denote the suggestion of the parameter settings to take the part including the range obtained from the success data set and not including the range suggested from the failure data set. And, the term of (Para_S) will represent the suggestion of the parameter settings to be the range obtained directly from the success data set. As for the term of (the part do not include Para_F), it will denote the suggestion of the parameter settings will taken the part not including the range obtained from the failure data set. Finally, the term of (*) will denote that the engineers need to make the detailed studies, e.g. the material analysis, the component evaluation, the resolution for the physical and the chemical properties.

Table 1. The judgment table.

		R_s Vs M_c	
		>	<=
R_f Vs m_c	>	Para_S – Para_F	The parts do not include Para_F
	<=	Para_S	* (need to make necessary detailed study)

<u>Step 3. Make recommendation for the parameter settings.</u>

After executing the step 2, we can obtain the recommendation about the parameter settings. Generally, we can obtain the rational range of the parameter settings we considered. It can be viewed as the mining result from the manufacturing process.

<u>Step 4. Make confirmation.</u>

After obtaining the recommendation of setting values, the practitioners can determine the final setting value according to the recommendation and the past engineering experiences. Then, confirmation experiments will be made. The practitioner can compare the obtained result and the expected result to judge the difference to be accepted or not.

4 Illustrative Example

4.1 Introduction

An illustrative example owing to a lead frame manufacturing company at HsinChu Science Park in Taiwan is employed to demonstrate the rationality of the proposed procedure. Figure 1 represents the final product after finishing the taping process. The number of the bubble or the size of the bubble in the tape can be two evaluation methods of the taping uniformity. The size of the bubble in the tape can not be directly measured by using the microscope. Hence, the process inspectors decide to use the number of the bubble in the tape to evaluate the taping uniformity. The taping uniformity will be divided into several classes according to the number of the bubble in the tape. Three classes are determined by the process engineers: the best uniformity (I), the acceptable uniformity (II) and the worst uniformity (III). The process engineers determine these classes with respect to results for the number of the bubble in the tape.

After discussing with the senior engineers, four process parameters are chosen by the process engineers: the pressure of the stamping down (A), the spacing between the tape cutting mode and the taping mode (B), the curing temperature (C) and the dwell time (D). Besides, several attributes of the manufactured product are also recorded like as the adhesive degree of tape (Att-1), the number of machine (Att-2), the copper quantity containing in lead frame (Att-3). Furthermore, the quality results of the taping for all pieces in one strip are inspected at every visual inspection. There are lots of items produced in line, and the engineers choose the SO (small outline) series to be the inspected items. The chosen SO series have six pieces in one strip and each piece has two tape, the total numbers of the tape in each strip are twelve. Six strips are sampled for each inspection. Hence, seventy-two tapes are inspected for each inspection. To study the parameter optimization of taping process, a project team including several senior engineers was grouped to perform this study. The engineers do the data collection about ten months when starting the project. These parameters' values are recorded and totally two hundred and seventy-eight data are collected. About one hundred and sixteen data are viewed as the failure data because that the corresponding quality response does not achieve the engineers' basic requirement. The record for those data will include the attributes of the manufactured products, the settings of parameters and the accumulated probabilities of the taping uniformity.

4.2 The operation of the proposed procedure

To simplify the operation, we summarize the related parameters of performing SOMNN in MATLAB: the number of processing elements for input layer is six (including three attributes and three accumulated probabilities), the number of inputting set is one hundred and sixty-two data for the success part (one hundred and sixteen data for the failure part), the number of processing elements for the self-organizing map layer is about 5×5 (too larger structure will lead the complexity to increase and too smaller structure will not represent it well, this parameter may need practitioners to try-and-error), the training epochs are 5000 and the training cycle is 25. Next, we will summarize the related parameter settings for the sixteen clusters. The criterion is taken as that the ratio of level settings are computed for each parameter. Then, the core functions of expert system can be constructed. Next, we get the information of the requirements being denoted as (0.8, 5, 75%, 0.8, 0.9, 1.0) to possess the analysis. We also set the maximum and minimum cutoff value Mc and mc to be 0.6 and 0.25 at first. After inputting the requirement into the expert system, then the recommendation can be obtained by such expert system. Herein, it will cluster into the seventh cluster for the success data set and the second cluster for the failure data set. The clustered result will be listed in Table 2. From Table 2, we can obtain the findings as:

(1) For parameter A: we can obtain parameter A to set as the range of LL (A0~A0+1.5 Kg/cm2).

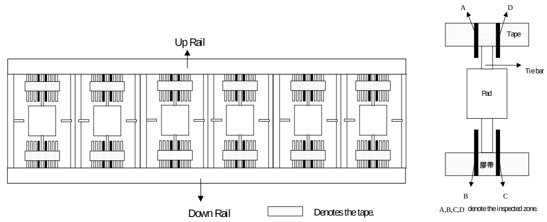

Fig. 1. The diagram of the final product after finishing the taping process.

Table 2. Clustered result

	Success data set		Failure data set	
	Level	R_S	Level	R_F
A	L	0.72*	LL	0.05
			LH	0.32*
	M	0.16	ML	0.20
			MH	0.11
	H	0.12	HL	0.17
			HH	0.15
B	L	0.69*	LL	0.29*
			LH	0.09
	M	0.14	ML	0.21
			MH	0.16
	H	0.17	HL	0.12
			HH	0.13
C	L	0.23	LL	0.16
			LH	0.20
	M	0.62*	ML	0.28*
			MH	0.11
	H	0.15	HL	0.14
			HH	0.11
D	L	0.26	LL	0.04
			LH	0.18
	M	0.66 *	ML	0.21
			MH	0.17
	H	0.18	HL	0.18
			HH	0.22

(2) For parameter B: we can obtain parameter B to set as the range of LH (B0 - 2 ~ B0 mil).

(3) For parameter C: we can obtain parameter C to set as the range of MH (C0+75~C0+100)℃.

(4) For parameter D: We can obtain parameter D to set as the range of M (D0–4~D0 sec).

4.3 Results

Then, engineers determine the setting values (A0+1.25, B0 – 1.5, C0+90, D0–2.5) according to the above recommendation and the past experience to perform the confirmed experiments. Six strips were sampled in the confirmed experiment and the average quality results (0.738, 0.836, 1.000) were very close to the ideal target (0.8, 0.9, 1.0). Restated, the rationality for using the business intelligence to support the parameter optimization via data mining technique can be demonstrated well in this study.

5 Concluding Remarks

As for the manufacturing processes, the potential intelligence, it was called as manufacturing intelligence or domain knowledge in this study, will include the information about process improvement or product development. Namely, mining such manufacturing intelligence will have positive contribution to enterprise's core competition. In this study, we proposed a data mining technique to mine the manufacturing intelligence to achieve the parameter optimization issue. The logistic thinking being taken is to mine the potential manufacturing intelligence during the process to help the practitioners improve their process performance and product quality. Besides, the potential manufacturing intelligence for the success manufacturing cases and failure manufacturing cases can also provide the different reference direction and information. The rationality and feasibility of the proposed procedure can also be demonstrated well according to the illustrative example in this study.

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