Handling Uncertainties in Modelling Manufacturing Processes with Hybrid Swarm Intelligence

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Abstract

Seldom research regarding manufacturing process modeling has considered the two common types of uncertainties which are caused by randomness as in material properties and by fuzziness as in the inexact knowledge in manufacturing processes. Accuracies of process models can be downgraded if these uncertainties are ignored in development of process models. In this paper, a hybrid swarm intelligence algorithm for developing process models which intends to achieve significant accuracies for manufacturing process modeling by addressing these two uncertainties is proposed. The hybrid swarm intelligence algorithm first applies the mechanism of particle swarm optimization to generate structures of process models in polynomial forms, and then it applies the mechanism of fuzzy least square regression algorithm to determine fuzzy coefficients on polynomials so as to address the two uncertainties, fuzziness and randomness. Apart from addressing the two uncertainties, the common feature in manufacturing processes, nonlinearities between process parameters, which are not inevitable in manufacturing processes, can also be addressed. The effectiveness of the hybrid swarm algorithm is demonstrated by modeling of the solder paste dispensing process.

Keywords: Fuzzy least square regression, particle swarm optimization, manufacturing process modeling, uncertainties, nonlinearities

1 Introduction

To maintain high quality on manufacturing new product, all key process variables relate to desired responses of the manufacturing process need to be understood and optimized, and an accurate manufacturing process model in describing the relationship between process variables and process responses is essential. Physical models, which establishes physical understanding of the manufacturing process and deploys the various physical laws, can be used to represent these relationships between process variables and process responses for manufacturing processes such as epoxy dispensing (Chen 2005, Chen 2002, Li et al. 2001), injection moulding process (Chiang et al.1991), solder paste dispensing process (Geren and Ekere 1994) and transfer moulding process (Han et al. 2000). However, physical models usually consist of partial differential equations with respect to both process variables and process responses, which may not be developed easily due to complex behaviours of certain manufacturing processes. Implicit process modelling approaches such as neural network modelling (Barajas et al. 2008, Li et al. 2006, Liukkonen et al. 2009), fuzzy logic modelling (Babets et al. 2000, Kang 1993, Xie and Lee 1994) and fuzzy neural network modelling (Giaquinto et al. 2009) can be used on generating implicit process models based on experimental data. These implicit process models consist of all equations in process simulators with an input-output black-box structure. However, these implicit process models are not very much appreciated by manufacturing engineers in process model development, because these implicit process models are in black-box nature which lack transparency and no explicit knowledge can be extracted directly from those developed process models.

Conventional statistical regression (Seber 2002), is a commonly used explicit modelling approach to generate explicit process models, which consist of equalities or inequalities in polynomial form. This explicit modelling approach is appreciated for manufacturing engineers to develop manufacturing process models based on experimental data, as the relationship between the inputs and outputs can be extracted from the equalities or inequalities. In statistical regression analysis, deviations between measured experimental data and estimates generated by statistical regression models are assumed to be caused by observation errors which are random variables with normal distributions, the usual assumption of statistical regression models. However, deviations can be caused due to indefinite structures of manufacturing processes or due to imprecise experimental data. In such case, uncertainty due to fuzziness cannot be addressed in the statistical regression models. Fuzzy regression (Tanaka and Watada 1988) is more appealing for developing the relationship between process variables and process responses, since the behaviours of manufacturing processes are fuzzy or measured experimental data is fuzzy in nature. In fuzzy regression, deviations between estimations and observed experimental data are assumed to be due to fuzziness of the model structure. Fuzzy regression has been used in an attempt to model many manufacturing processes, especially those processes which have a high degree of fuzziness due to the involvement of processes of material such as die-casting process (Lai and Chang 1994), epoxy dispensing process (Ip et al. 2003 (b), Kwong and Bai 2005) and transfer moulding process (Ip et al. 2003(a)).

Investigation has been conducted regarding characteristics and differences between statistical regression approaches and various fuzzy regression approaches

(Chang 2001(b)). Based on comparative assessment, the fundamental differences between statistical regression and fuzzy regression approaches have concluded that estimates generated by statistical regression models consist of the random type of uncertainty and estimates generated by fuzzy regression models consist of the fuzziness type of uncertainty. In order to integrate both random and fuzzy types of uncertainty into one regression model, a fuzzy least-squares regression was introduced by Chang (Chang and Ayyub (a), Chang 2001(b)) to model manufacturing processes which can address both the fuzziness and the randomness of a system in the development of a fuzzy least-squares regression model. However, both fuzzy least square regression and conventional fuzzy regression approaches can only generate models in fuzzy linear polynomial form which only consists of a set of fuzzy linear terms but do not consist of fuzzy nonlinear terms. Therefore, the existing fuzzy least-squares regression approach or conventional fuzzy regression approach are not appropriate to develop models because both approaches can not address the nonlinear nature of manufacturing process systems. In fact, nonlinear behaviors between process variables are generally unavoidable in manufacturing processes. If nonlinear terms are considered in the approach of fuzzy least-square regression, more accurate fuzzy regression models are likely to be developed.

In this paper, a hybrid swarm intelligence algorithm has been proposed to develop process models which intend to overcome the limitations of the commonly used explicit modeling approaches, statistical regression and fuzzy regression. The hybrid swarm intelligence algorithm intends to address uncertainty due to both fuzziness and randomness in manufacturing process systems and nonlinearity in manufacturing process systems. The swarm intelligence algorithm mainly consists of two mechanisms based on particle swarm optimization and fuzzy least squares regression. The swarm intelligence algorithm generates structures of process models in nonlinear polynomial forms based on the operations of particle swarm optimization, which are identical to those of the original PSO (Eberhart and Kennedy 1995) except that the elements of individuals are represented by arithmetic operations and variables of manufacturing process models. This representation is one of the forms of grammatical evolution (Neill and Brabazon 2006), which can be used to represent models in a polynomial form. After defining the nonlinear polynomial form of the process model, the fuzzy least squares regression (Chang 2001(b)) is conducted to determine fuzzy coefficients of the process model in which the uncertainty due to both fuzziness and randomness of the manufacturing process model can be addressed.

The proposed swarm intelligence algorithm was implemented on a prototype system and its effectiveness was evaluated by modeling the solder paste dispensing process in electronic packages, which is a highly nonlinear manufacturing process, because of the reactive nature of solder paste compounds and complex geometries of inserts in dispensing. A proper process model of solder paste dispensing process, is critical to provide a fundamental understanding of relationships between process variables and process responses, and is helpful to determine proper process parameters. Modeling results obtained by the hybrid swarm intelligence algorithm is compared with those based on the other commonly used methods for generating explicit models for dispensing processes in electronic packaging.

2 Hybrid swarm intelligence algorithm

This section first discusses the experimental data required by the hybrid swarm intelligence algorithm to generate process models. Then the features of the process models generated by the hybrid swarm intelligence algorithm, which are in fuzzy nonlinear regression form, are presented. Finally the mechanism of the hybrid swarm intelligence algorithm is discussed.

2.1 Experimental data

Before conducting experiments, experimental planning needs to be performed to determine what kind of experimental data is required to be collected, so that the process model generated by the hybrid swarm intelligence algorithm are appropriate for the manufacturing process design. It is required to determine the most interested process response y and to specify the significant process variables x_1, x_2 , … , x_N , which are included in the experiments to determine their effects with respect to the process response y. The factor levels for the process variables are usually specified into two or three levels. Full factorial designs with m replications which allow hypothesis testing of all process variable effects and all possible process variable effects on the process response are used to address the uncertainty due to randomness of the manufacturing process. The number of levels and the number of replications m are usually determined based on the availability of time and cost for conducting the experiments and also the precision requirement of the process model. If the uncertainty due to randomness does not exist in the manufacturing process, the experimental results will have no difference in all replications of the experimental results. However, if the uncertainty due to randomness does exist in the manufacturing process, differences between experimental results can be found in some replications of experiments. Therefore, the uncertainty due to randomness of the manufacturing process can be addressed based on the experimental results.

After conducting the experiments, the experimental data can be collected and the experimental data for the k-th replication is illustrated in Table 1, where k =1, 2, … n. The i-th experimental data set in the k-th replication is denoted as $\{y_i^d(k), x_{i1}^d, x_{i2}^d, ..., x_{iN}^d\}$, and the i-th experimental data set in fuzzy number form is defined as $\{(y_i^d, e_i^{d,L}, e_i^{d,R}), x_{i1}^d, x_{i2}^d, ..., x_{iN}^d\}$, where i=1, 2, …2^N. The value of the dependent variable $(y_i^d, e_i^{d,L}, e_i^{d,R})$, which includes the left spread $e_i^{d,L}$ and right spread $e_i^{d,R}$ of the process response y_i^d, are fuzzy rather than crisp. y_i^d can be calculated based on equation (1). The left spread $e_i^{d,L}$ and the right spread $e_i^{d,R}$ can be determined based on equations (2) and (3) respectively.

$$y_i^d = \frac{1}{n}\sum_{k=1}^{n} y_i^d(k), \qquad i = 1,2,...2^N \tag{1}$$

$$e_i^{d,L} = y_i^d - \min_{k=1,...,n} y_i^d(k), \quad i = 1,2,...2^N \tag{2}$$

$$e_i^{d,R} = \max_{k=1,...,n} y_i^d(k) - y_i^d, \; i = 1,2,...2^N \tag{3}$$

Figure 1 summarizes the mechanism on collecting experimental data to generate process models based on the hybrid swarm intelligence algorithm.

2.2 Process models

The aim of hybrid swarm intelligence algorithm is to generate a process model in fuzzy nonlinear regression form which can be written as follows:

$$\tilde{y} = \tilde{f}_{NR}(x) = \tilde{A}_0 + \sum_{i_1=1}^{N} \tilde{A}_{i_1} x_{i_1} + \sum_{i_1=1}^{N}\sum_{i_2=1}^{N} \tilde{A}_{i_1 i_2} x_{i_1} x_{i_2} + \sum_{i_1=1}^{N}\sum_{i_2=1}^{N}\sum_{i_3=1}^{N} \tilde{A}_{i_1 i_2 i_3} x_{i_1} x_{i_2} x_{i_3} + \ldots \sum_{i_1=1}^{N} \ldots \sum_{i_d=1}^{N} \tilde{A}_{i_1 \ldots i_d} \prod_{j=1}^{d} x_j \tag{4}$$

where $\tilde{y}$ is the process response; x_k is the k-th process variable with k=1,2, …N; $\tilde{A}_0 = \left(\alpha_0, c_0^R, c_0^L\right)$, $\tilde{A}_1 = \left(\alpha_1, c_1^R, c_1^L\right)$, $\tilde{A}_2 = \left(\alpha_2, c_2^R, c_2^L\right)$,…, $\tilde{A}_N = \left(\alpha_N, c_N^R, c_N^L\right)$, $\tilde{A}_{11} = \left(\alpha_{11}, c_{11}^R, c_{11}^L\right)$, $\tilde{A}_{12} = \left(\alpha_{12}, c_{12}^R, c_{12}^L\right)$, … $\tilde{A}_{NN} = \left(\alpha_{NN}, c_{NN}^R, c_{NN}^L\right)$,… $\tilde{A}_{N\ldots N} = \left(\alpha_{N\ldots N}, c_{N\ldots N}^R, c_{N\ldots N}^L\right)$ are the fuzzy coefficients. $\tilde{A}_{i_1}$ is the linear fuzzy coefficient for the variable x_{i_1}; $\tilde{A}_{i_1 i_2}$ is the fuzzy coefficient regarding interaction between the two variables x_{i_1} and x_{i2}; and $\tilde{A}_{i_1 i_2 i_3}$ is the fuzzy coefficient regarding interaction between the three variables x_{i_1}, x_{i_2} and x_{i_3} etc. All α are the center of the fuzzy coefficient, and all c^R and c^L are the right and left spreads of the fuzzy coefficients respectively. The detailed description of the nonlinear regression form formulated in (4) can be referred to Section 2 of (Chan et al. 2010). Based on the fuzzy nonlinear regression shown in equation (4), the two features, namely the degree of fit with respect to the experimental data and the fuzziness of each process parameter of the manufacturing process, can be addressed (Tanaka and Watada 1988). Also the nonlinearity between the process parameters can also be addressed by the interaction and high order terms in equation (4). Since some terms in equation (4) may be redundant, prudent selection of significant terms or orders is advisable if a more parsimonious and adequate model is desired. In this paper, the hybrid swarm intelligence algorithm is proposed to select significant terms in equation (4). The mechanism of the hybrid swarm intelligence algorithm is discussed in the following sub-section.

2.3 Mechanism of hybrid swarm intelligence algorithm

The hybrid swarm intelligence algorithm mainly consists of two components, particle swarm optimization (Eberhart and Kennedy 1995) and fuzzy least square regression (Chang and Ayyub 2001, Chang 2001). It first uses the mechanism of particle swarm optimization to generate structures of process models in nonlinear polynomial form in which nonlinearities between process parameters can be addressed. Then it uses the mechanism of fuzzy least square regression to determine the fuzzy coefficients of the nonlinear polynomials, which can address the two uncertainties due to both the fuzziness and randomness of the manufacturing processes. Therefore the process models generated by the hybrid swarm intelligence algorithm are able to address the two uncertainties, fuzziness and randomness, and the nonlinearities between process variables. The flow of the hybrid swarm intelligence algorithm is shown in Figure 2.

In Step 1, the hybrid swarm intelligence algorithm uses the mechanism of PSO to create N_{pop} random initial particles $P_1^g, P_2^g, \ldots, P_{N_{pop}}^g$ at the first generation with g = 1. All particles are in the form $P_i^g = \left(p_{i,1}^g, p_{i,2}^g, \ldots, p_{i,N_p}^g\right)$ where $p_{i,k}^g$ with k =1, 2, …, N_p is randomly generated in the range between 0 to 1.

In Step 2, each particle is transformed into a polynomial structure represented by the variables of the process model (x_1, x_2, …, and x_m) and the arithmetic operations (‘+’, and ‘*’) as defined in equation (4) based on (Kennedy and Eberhart 1997). m is the number of variables of the system model. In each particle, the odd number elements, $p_{i,1}^g$, $p_{i,3}^g$, …, p_{i,N_p}^g, represent variables of the polynomial structure, and the even number elements, $p_{i,2}^g$, $p_{i,4}^g$, …, p_{i,N_p-1}^g, represent the arithmetic operations, where N_p is the number of elements in a particle and is an odd number. N_p is always larger than m. For the k-th odd number element $p_{i,k}^{g}$, no variable is represented by $p_{i,k}^{g}$, if $0 < p_{i,k}^{g} \leq 1/(m+1)$. The k-th odd number element $p_{i,k}^{g}$ represents the *l-th* variable, x_l, if $l/(m+1) < p_{i,k}^{g} < (l+1)/(m+1)$ with l>0. For the k-th even number element $p_{i,k}^{g}$, if $0 < p_{i,k}^{g} \leq 1/2$ and $1/2 < p_{i,k}^{g} \leq 1$, $p_{i,k}^{g}$ represents the arithmetic operations '+' and '*' respectively. The number of elements in each particle N_p is determined based on the trial and error method.

In Step 3, the fuzzy coefficients, $A_0^{i,g} = \left(\alpha_0^{i,g}, c_0^{R,i,g}, c_0^{L,i,g}\right)$, $A_1^{i,g} = \left(\alpha_1^{i,g}, c_1^{R,i,g}, c_1^{L,i,g}\right)$, $A_2^{i,g} = \left(\alpha_2^{i,g}, c_2^{R,i,g}, c_2^{L,i,g}\right)$, … and , $A_{N_i^g-1}^{i,g} = \left(\alpha_{N_i^g-1}^{i,g}, c_{N_i^g-1}^{R,i,g}, c_{N_i^g-1}^{L,i,g}\right)$, in the polynomial structure represented by the i-th particle at the g-th generation are generated based on the hybrid fuzzy least-squares regression developed by (Chang and Ayyub 2001, Chang 2001). $\alpha_k^{i,g}$ is the center of the k-th fuzzy coefficient $A_k^{i,g}$ of the i-th particle at the g-th generation, $c_k^{R,i,g}$ and $c_k^{L,i,g}$ is the right spread and the left spread of $A_k^{i,g}$. The hybrid fuzzy least-squares regression can feature the capability of dealing with the two types of uncertainty which is associated with randomness and fuzziness in manufacturing processes. The detailed operations of the hybrid fuzzy least-squares regression can be referred to ((Chang and Ayyub (a), Chang 2001(b)).

In Step 4, the fitness of each particle is evaluated. The j-th particle at generation g is evaluated by measuring how well the model represented by the particle can fit the experimental data conducted on the manufacturing process system. The following fitness function, which is incorporated with penalty terms suggested by (Madar et al 2005) is used and is defined as:

$$fitness_i^g = \frac{\left(1 - MRAE_i^g\right)}{\left(1 + \exp\left(c_1\left(L_j - c_2\right)\right)\right)} \tag{5}$$

where $fitness_i^g$ is the fitness value of the i-th particle, L_i is the number of arithmetic operations of the model represented by the i-th particle, c_1 and c_2 are both penalty terms, and MRAE_j^g is mean relative absolute error of the j-th particle at generation g. MRAE_j^g is denoted as:

$$\mathrm{MRAE}_j^g = 100\% \times \frac{1}{n_{train}} \sum_{k=1}^{n_{train}} \left| \frac{y(k) - f_i^g(\mathbf{x}(k))}{y(k)} \right| \tag{6}$$

where f_i^g is the process model represented by the j-th particle at generation g, and n_{train} is the number of data points used to compute the fitness function.

In Step 5, the velocity of each particle is updated. The velocity $v_{i,k}^g$ (corresponding to the flight velocity in a search space) of the k-th element $p_{i,k}^g$ of the i-th particle P_i^g at the g-th generation is updated by the following formula:

$$v_{i,k}^g = \begin{cases} \hat{v}_{i,k}^g, \text{if } v_{\max} > \hat{v}_{i,k}^g > v_{\min} \\ v_{\max}, \text{if } \hat{v}_{i,k}^g > v_{\max} \\ v_{\min}, \text{if } \hat{v}_{i,k}^g < v_{\min} \end{cases} \tag{7}$$

where $\hat{v}_{i,k}^g = w \cdot v_{i,k}^{g-1} + \phi_1 \cdot rand(\ ) \cdot \left(pbest_{i,k} - p_{i,k}^{g-1}\right) + \phi_2 \cdot rand(\ ) \cdot \left(gbest_k - p_{i,k}^{g-1}\right)$; k = 1,2, …, N_{pop}; $pbest_i = \left[pbest_{i,1},\quad pbest_{i,2},\quad \ldots\quad pbest_{i,N_p}\right]$ is the best previous position of the i-th particle recorded so far from the previous generation; $gbest = \left[gbest_1,\quad gbest_2,\quad \ldots\quad gbest_{N_p}\right]$ is the position of the best particle among all the particles; *rand*() is a uniform random function which generate a random number in the range of [0,1]; $v_{\min}$ and $v_{\max}$ determine the resolution with which regions are to be searched between the present position and the target position; w is an inertia weight factor; ϕ_1 and ϕ_2 are acceleration constants (Eberhart and Shi 1998); w is the inertia weight (Eberhart and Shi 2000).

In Step 6, the position of the k-th element $p_{i,k}^{g}$ of the i-th particle P_i^g at the g-th generation are calculated by the following formula, which updates the previous position of the particle based on the current velocity of the particle:

$$p_{i,k}^{g} = p_{i,k}^{g-1} + v_{i,k}^{g} \tag{9}$$

In Step 7, the fitness of each particle is evaluated by conducting Step 3 and Step 4.

In Step 8, the termination criterion is met when the number of generations is equal to a pre-defined number of generations G. Otherwise, the hybrid swarm intelligence algorithm goes to Step 5 and the generation number g is increased by 1, i.e. $g \leftarrow g+1$.

3 Modeling of solder paste dispensing process using the hybrid swarm intelligence algorithm

To evaluate the effectiveness of the hybrid swarm intelligence algorithm to modeling manufacturing processes, it is employed to model a solder paste dispensing process used in electronic manufacturing. The modeling results are compared with those based on the commonly used methods for generating explicit models for fluid dispensing processes.

3.1 Solder paste dispensing process

In electronic packaging, solder paste is the primary means for providing interconnection between surface mount component leads and print circuit board pads in surface mounting and the solder paste dispensing is recommendable (Chen et al. 2005). The solder paste joint provides the electrical, thermal and mechanical connection between the surface mount components and the electronic circuit. The reliability of the solder paste joint can be determined by controlling its shape. The solder volume dispensed is thus the single most important variable in controlling the shape of a surface mount solder joint. If the correct amount of solder is deposited, the ideal shape can be formed and the joint can be inherently reliable. Conversely, if excess solder is applied, the joint will be rigid and unreliable or bridging will occur. Solder paste dispensing is precise quantities of solder paste on the pads and to ensure that the correct solder joints are formed after reflow.

Two main factors determine the solder paste dispensing requirements in the automated rework cell: the size of surface mount component pads and the operating variables of the solder paste dispenser (Geren and Ekere 1994). In order to provide precise and consistent solder paste volumes, the process parameters of the dispensing equipment must be properly characterized to establish the empirical relationship between various pad sizes and the operating variables of the dispenser. The empirical data are then held in the cell controller and used for operating the solder paste dispenser. However, controlling the volume of the solder paste is a highly complex manufacturing process, because solder paste involves more than 10 influential material properties and an accurate rheological description of fluid of solder paste is difficult to be obtained. Also some process parameters such as soldering temperature could be affected by environmental effects easily. For example, change of room temperature and air ventilation could lead to fluctuation of soldering temperature. The solder paste must be stored and handled properly. Exposing the solder paste to extreme heat or cold can change the physical properties of the paste. Exposure to moisture or vibration can also cause a problem. The causes of these dispensing problems can often be linked to one another and often times take several hours to show up. Therefore development of an accuracy model for the solder paste dispensing process is necessary.

A schematic diagram of a solder paste dispensing system using the rotary feed screw principle is investigated in this research and is shown in Figure 3. The solder paste is held in a feed reservoir (a) under a positive head of air. This positive air pressure, supplied by the air line (g) forces the pasty fluid out of the feed reservoir into the vertical feed shaft of the valve body (b), and then the pasty fluid is injected from the angled feed shaft (c), to the feed screw chamber (d). The solder paste fluid from the chamber to the dispense point (e) is dispensed by the feed screw rotation in the feed direction, which is driven by the DC motor (f). A specific volume of solder paste fluid is controlled by applying a DC voltage signal to the DC motor which rotates the feed screw. The amount of solder paste deposited can be controlled by the amount of time in which the clutch is engaged and is called the shot size. Also the amount of solder paste which exits through the interchangeable needle can be controlled by selecting with different sizes of needles with different diameters.

To control volume of the solder paste, the four most significant process variables for the solder paste dispensing process are identified as pressure x_1, needle inner diameter x_2, shot size x_3 and dwell time x_4. The response output of the process y, the volume of the solder paste is indicated by the diameter of the circular solder pad. In the experimental plan, each process variable is divided into two levels. For the pressure x_1, 0.276 bar and 0.827 bar are defined as level 1 and level 2 respectively. For the needle inner diameter x_2, 0.041 mm and 0.584 mm are defined as level 1 and level 2 respectively. For the short size x_3, 150 ms and 500 ms are defined as level 1 and level 2 respectively. For the dwell time x_4, 0 ms and 500 ms are defined as level 1 and level 2 respectively.

Full factorial designs regarding the four operating parameters with five replications were conducted. The four operating parameters x_1, x_2, x_3 and x_4 are normalized to [0,1], and their resulting values are shown in Table 2. While the hybrid swarm intelligence algorithm is applied to modeling the solder paste dispensing process, the values of dependent variables are fuzzy instead of crisp, which can be represented as $\left(y_j, e_j^L, e_j^R\right)$, where y_j can be calculated based on (1), and e_j^L and e_j^R can be determined respectively based on (2) and (3).

3.2 Implementation of the hybrid swarm intelligence algorithm

The proposed hybrid swarm intelligence algorithm to generate models for manufacturing processes was implemented using MATLAB and a prototype system was developed based on the proposed hybrid swarm intelligence algorithm. The parameter settings of the hybrid swarm intelligence algorithm, which is referred in (Neill and Brabazon 2006), were utilized to generate the models for manufacturing processes: number of particles in the swarm = 500; number of elements in the particle = 30; inertia upper and lower weight factor, $w_{\max}$ and $w_{\min}$ = 0.90 and 0.4 respectively; acceleration constants φ_1 and φ_2 = 1; maximum velocity $v_{\max}$ = 0.2; dimensions of the particles = 100. The pre-defined number of generations is determined based on the trial and error method. If the modelling error obtained by the hybrid swarm intelligence algorithm is not satisfactory, the pre-defined number of generations can be increased until a satisfactory modelling error is achieved.

Because the number of existing process variables in the soldering paste dispensing process is 4 which are not a large number, the total number of generation of the hybrid swarm intelligence algorithm is pre-defined as 20.

To run the prototype system, the number of process parameters (which is 4), number of experimental data (which is 16) and number of replications (which is 5) are inputted first. Then the experimental data and results which are described in Table 2 are inputted to the prototype system. As the hybrid swarm intelligence algorithm is a stochastic algorithm, different results can be obtained with different runs. Therefore the hybrid swarm intelligence algorithm was run for 30 times, and the results among the 30 runs were recorded. After performing all the computations of the hybrid swarm intelligence algorithm, the model with the lowest training error was generated as shown in Tables 3 for the solder dispensing process

Apart from using the hybrid swarm intelligence algorithm, the five commonly used algorithms for generating explicit models for dispensing processes were employed as a comparison. The five algorithms were also implemented with Matlab programming software and they are described as follows:

a) Statistical regression (SR) (Seber 2003), which is a commonly used modeling approach to develop explicit models in linear polynomial forms. SR has been used on modeling the epoxy dispensing process for microchip encapsulation in electronic packaging (Kwong et al. 2007).
b) Peters' fuzzy regression (P-FR) (Peters 1994), which is an extension of the original fuzzy regression (Tanaka and Watada 1988). Based on P-FR, the estimated interval on the generated fuzzy linear model is influenced by all training data and the

generated fuzzy linear model is robust in the presence of outliers. P-FR has been used in modeling the transfer moulding for microchip encapsulation in electronic packaging (Ip et al. 2003(b)).

c) Chang' fuzzy regression (C-FR) (Chang 2001(a)), which can generate fuzzy regression model in which the fuzzy coefficients can address both fuzziness and randomness of the experimental data. C-FR has been used in modeling the solder dispensing process for electronic packaging (Kwong et al. 2008).

d) Genetic programming (GP) (Madar et al. 2005), which can generate empirical models in nonlinear polynomial forms. Based on the GP, the structures of the polynomials of the solder dispensing process are represented as a hierarchical tree form, which are composed of functions F and terminals T (Koza 1992). The solder dispensing process model contains the two arithmetic operations, +, and *, thus F is represented as $F = \{+, *\}$. The set of terminals T contains the process variable set $\boldsymbol{x}=\{ x_1, x_2, \ldots x_4\}$ of the solder dispensing process. The structures of the polynomials of the solder dispensing process are depicted as a labeled tree with ordered branches. In the tree, operations from the function set F are used as internal nodes, and arguments from the terminal set T are used as terminal nodes. Polynomial structures are generated by the evolutionary operations, and the coefficients of the polynomials are determined by the least squares method. The following parameters with reference to (Madar et al. 2005) were used in the GP: population size =100; probability of crossover = 0.5; probability of mutation= 0.5. The number of computational evaluations used in the GP was the same as the one used in the hybrid swarm intelligence algorithm.

e) A neural network (NN) was also used to model the solder dispensing process. A three-layer feed-forward NN was constructed with four input neurons as the four process variables (x_1, x_2, … x_4) and a neuron in the output layer as the process response y. The NN was developed based on the Levenberg Marquardt algorithm (Lera and Pinzolas 2002) which is a popular training algorithm for feed-forward neural networks. The following parameters were used for developing the neural network: number of iterations used in the Levenberg Marquardt algorithm = 100, and number of hidden nodes used in the NN = 10.

Table 3 summarizes all the mean relative absolute errors and the variances of relative absolute errors of all the six tested algorithms, SR, P-FR, C-FR, GP, NN and the proposed hybrid swarm intelligence algorithm. From Table 4, it can be seen that both the mean relative absolute error and the variance of relative absolute errors of the hybrid swarm intelligence algorithm are smaller than those obtained by the other five tested algorithms. Since NN is a black-box typed model, no explicit model form can be presented. It can also be noted that both the linear and nonlinear terms can be generated by the hybrid swarm intelligence algorithm, while only the linear terms can be generated by SR, P-FR and C-FR. This indicates that the hybrid swarm intelligence algorithm can fit the experimental data sets with the mean relative absolute error and the variance of relative absolute errors.

To validate the generalization capability of the hybrid swarm intelligence algorithm, cross validations were conducted on the six algorithms. 4 experimental data sets were randomly selected from the whole 16 experimental data sets as the validation data sets, which are shown in Table 4. The remaining 12 experimental data sets were used to develop models based on the six algorithms, SR, P-FR, C-FR, GP, NN and the hybrid swarm intelligence algorithm. The validation errors regarding the mean absolute relative errors were calculated. The validations were repeated 12 times. We ran the hybrid swarm intelligence algorithm 30 times in each validation test and the mean of the 30 runs was calculated. Table 4 summarizes the validation errors of the four methods. The testing errors for the 10 test runs are also shown in Figure 4. From the table, it can be seen that the hybrid swarm intelligence algorithm yields the smallest mean validation error and the smallest variance of validation errors comparing with those yielded by the other three tested algorithms. This indicates that the hybrid swarm intelligence algorithm has higher generalization capability when comparing with the other five tested algorithms.

4 Conclusion

In this paper, a hybrid swarm intelligence algorithm is developed based on the particle swarm optimization and fuzzy least square regression algorithm for generating models for manufacturing processes. It intends to deal with two types of uncertainties in developing models for manufacturing processes: fuzziness and randomness, which are associated with modeling manufacturing processes. It also intends to generating proper nonlinear terms, while previous studies only yield fuzzy linear regression based process models in which nonlinear terms are included. The hybrid swarm intelligence algorithm mainly operates with two mechanisms. First it employs the mechanism of the particle swarm optimization to generate structures of the process models in polynomial forms in which both linear and nonlinear terms can be included. Then it employs the mechanism of fuzzy least square regression algorithm to determine fuzzy coefficients on the polynomial in which the two uncertainties due to the fuzziness of the manufacturing processes and the randomness caused by conducting the experiments can be addressed.

To evaluate the effectiveness of the proposed hybrid swarm intelligence algorithm to modeling manufacturing processes, it has been implemented on a prototype system to apply on modeling of the solder paste dispensing process. The results obtained by the hybrid swarm intelligence algorithm were compared with those obtained by the other commonly used explicit modeling methods, statistical regression, fuzzy linear regression and fuzzy least square regression, genetic programming and neural network The result shows that the smallest number of training errors can be achieved by the proposed hybrid swarm intelligence algorithm. This indicates that the hybrid swarm intelligence algorithm is more capable to fit the data sets than the other methods. Also a comparison of the cross-validation results show that the smallest prediction errors and errors in variance can be achieved by the hybrid swarm intelligence algorithm than those obtained by the other tested explicit modeling methods. In future work, the effectiveness of the hybrid swarm intelligence algorithm will be future validated by modeling epoxy dispensing process which is a highly nonlinear and complex encapsulation process for electronic packaging.

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