J Intell Manuf (2019) 30:441–457
https://doi.org/10.1007/s10845-016-1257-3

Steepest ant sense algorithm for parameter optimisation of multi-response processes based on taguchi design

P. Luangpaiboon[1] · S. Boonhao[1] · R. Montemanni[2]

Received: 14 February 2016 / Accepted: 24 August 2016 / Published online: 31 August 2016

Abstract Due to the continuous refinements in engineering operations, process parameters need to be optimised in order to improve the production quality. In this study we present a novel method based on the hybridisation of an ant colony system search mechanism with a steepest ascent method to achieve such a parameter optimisation. The proposed algorithm has been implemented and run on two real time industrial applications. Experimental results showed that the optimised parameters for a stealth laser dicing process provided by the new method were able to increase the production quality by improving production precision, which is measured in terms of average deviation from the expected result and relative variance. The novel method we propose was able to identify improved settings for a stealth laser dicing process with five parameters, resulting in a greatly reduced rate of product failures. Additionally six parameters were optimised for another industrial application, namely a grease filling system with twin towers, using only 23 experiments, leading to an increase in the tool life (objective of the optimisation) from the previous average of 9236 U produced to 13,883 U. The new method performed better than conventional response surface methods, showing therefore to be promising for other similar industrial applications.

✉ P. Luangpaiboon
lpongch@engr.tu.ac.th;
pongchanun.luangpaiboon@hotmail.com

S. Boonhao
amp4656@hotmail.com

R. Montemanni
roberto@idsia.ch

1 Industrial Statistics and Operational Research Unit (ISO-RU), Department of Industrial Engineering, Faculty of Engineering, Thammasat University, Pathumthani 12120, Thailand

2 Dalle Molle Institute for Artificial Intelligence (IDSIA), University of Applied Sciences of Southern Switzerland (SUPSI), Galleria 2, Manno 6928, Switzerland

Keywords Taguchi design · Multiple linear regression · Desirability function · Steepest ant sense · Stealth laser dicing · Twin grease filling system

Introduction

Seeking global solutions of continuous optimisation problems arise in many industrial applications. Response surface methods have been used to solve a vast variety of practical problems. Practitioners often wish to determine the proper levels of process parameters at which the responses approach their optimum. A combination of mathematical and statistical techniques aims to model and predict the response of interest, that is affected by a number of process parameters in need of tuning (Myers et al. 2016). The optimum is typically determined from a particular function in terms of those parameters via common statistical tools. Factorial design methodology (FDM) employs full or fractional factorial design and avoids the traditional one-factor-at-a-time experiments (Montgomery 2012). The statistically significant main or interaction effect between variables is a frequent phenomenon to drive the process to its optimum. Instead of the traditional full or fractional factorial experiments which were used by the majority of previous researchers to determine the individual effect of various parameters on continuous problems, Taguchi designs can be employed to reduce the number of designed experiments, time and overall related cost. Taguchi method (TM) is the reference method in the literature to achieve a robust parameter design for production processes in industry. The method is systematic, efficient and insensitive to variation. The target in such applications is to determine an optimal configuration of a large number of parameters, while minimising the number of experiments on the real machines in such a way that the production can be carried out at high quality standards and at low cost. This class of methods is based on a sequence of experiments designed to gain very useful information on a decreasing number of experimental parameters and design points. The initial experiment is often limited to a small subregion of the feasible operating region for the process or system of interest. In such cases, a first order model often allows an adequate approximation to the response surface. Moving toward a region of rapidly improved response can be directly accomplished by following the path of steepest ascent (descent), according to the theoretical model of the system.

Many of the applications in the literature treat a single response or quality characteristic, which is considered critical. In today's highly competitive markets, there is often more complexity in the product or process design. The simultaneous optimisation of several responses upon a number of parameters or sets of operating conditions needs to be achieved. To reach a satisfactory compromise of multiple conflicting responses in an actual manufacturing process, a recent thrust of management has focused on the use of a desirability function approach to combine various criteria into a single one with the objective of maximising multiple response measures simultaneously. Although the conventional response surface methods provide useful tools, they are usually unsuitable for finding a global optimum of a continuous optimisation problem with several local optima or curved ridges. In the last few years, population-based metaheuristic algorithms have been widely used in many applications in place of traditional techniques. To improve upon the efficiency of the steepest ascent method (SAM) for continuous optimisation problems, researchers made some efforts to hybridise SAM with some neighbourhood-search-based procedures such as genetic, simulated annealing, tabu search, and ant colony optimisation. In order to overcome the deficiencies of mathematical and statistical techniques of the SAM, metaheuristic optimisation techniques based on ant colony systems have been proposed. These allow a good solution or near optimum to be achieved within a reasonable execution time, without any loss of subtle characteristics of the first order model and without any requirement of complex derivatives or careful choice of initial values.

The proposed algorithm based on the hybridisation of Taguchi design, steepest ascent (descent) and ant colony systems could help to improve and simplify the continuous optimisation procedures. The objective of the present study is to develop a new approach that systematically determines suitable parameter levels for process optimisation problems. With this novel algorithm, a set of influential parameters is obtained by which the generated model closely reproduces process responses. Practically, it starts with various classes of experimental designs. In this research, Taguchi orthogonal arrays are implemented to determine those parameters having impacts on the process responses. The first order relationships between the statistically significant parameters and process responses are then estimated using the method of least squares. An optimisation method based on the path of steepest ascent or descent is used to determine an optimum set of process parameters that gives the best responses of a model. Due to the complexity involved in the real industrial process, good functional relationship with reasonable accuracy between responses and process parameters is difficult to obtain. Once the solutions deteriorate, the set of new solutions from stochastic mechanisms from ant colony systems is used to perform experiments rather than terminate the sequential optimisation procedures. The proposed method has been tested on actual industrial applications and the experimental results compared favourably to the results from conventional response surface methods, verifying the adequacy of the solution and also the applicability of the newly devised method. The rest of the paper discusses the following: "Related methods" section introduces Taguchi design, the steepest ascent method (SAM), and the ant colony system (ACS). "The new steepest ant sense algorithm (SASA)" section describes the novel integrated approach for a multi-response optimisation with continuous improvement that uses evolutionary operations. In "Industrial applications of the SASA and comparison with other methods" section the proposed algorithm is tested on two real industrial processes, namely, a laser dicing operation and a grease filling system, where process parameters need to be set to meet all quality requirements. Results are compared with those of conventional methods. "Conclusions" are finally summarised in last section.

Related methods

A collection of statistical and mathematical techniques is conventionally used to develop, improve and optimise industrial systems in the context of response surface methodologies. Its objective is to evaluate a response influenced by several parameters. Taguchi orthogonal arrays are experimental designs employed for a first-order or second-order response surface. Although there are many available types of plans, such as the complete or fractional factorial design, the potential benefit of Taguchi design approaches is its ability to solve complex systems with a drastically decreased number of performed experiments when compared to previous experimental designs. The response surface of a process is usually described by a polynomial representation. Moreover, it is assumed that the current operating region of the problem of interest is far from the optimum. The optimisation resolution process time can be reduced by assessing responses and the corresponding parameters through a first-order approximation, rather than using more complex empirical models. Gradient descent (ascent) or steepest descent (ascent) obtained by the designed experiments and principles of least squares are often adequate for rapidly moving toward a region of improved responses. After an adequate model is obtained, it then becomes necessary to design a trajectory towards the optimum.

Some real problems need the best solution simultaneously assessed by several fundamentally conflicting responses. In many cases, there are multiple constraints and noisy environment, owing to increasing the complexity of product and process development (Sibalija and Majstorovic 2012). However, response surface methodology is unable to directly deal with these problems. To overcome these difficulties, existing stochastic mechanisms from metaheuristics are employed. Ant colony system optimisation has been successfully used to solve various combinatorial optimisation problems. However, very little exists in terms of documentation for solving continuous optimisation problems. In this study, ant colony systems allow the exploration of a combination with another simple optimisation method based on steepest ascent (descent). The following paragraphs review the traditional approaches for response surface optimisation that are later embedded into the new framework we propose.

Taguchi design

Taguchi method (TM) includes both experimental designs and analyses and has been used by various industries for many years (Taguchi et al. 1993). These applications include cryogenic treatment and drilling parameters of AISI 304 stainless steel affecting surface roughness and roundness error based on drilling parameters and heat treatments (Çiçek et al. 2015). There have been various successful applications of TM to industrial processes, such as the setting of optimised factors affecting coagulation in a haemodialyser (Lin et al. 2016) and wastewater treatment (Zirehpour et al. 2014) including the specific film parameter optimisation (Kuo et al. 2016). It uses fractional factorial designs or orthogonal arrays on the full set of parameters affecting the output performances or responses. This method categorises influential parameters into *controllable* parameters and *uncontrollable* parameters (noise). For system stability, the controllable parameters are used to determine the preferred designed plan. With no parameter interaction, the selection of Taguchi designed orthogonal arrays depends on the number of controllable parameters and their levels. When considering system variations, the decision maker aims at reducing the effects of uncontrollable parameters via various design alternatives. The objectives of Taguchi design are simultaneously to improve quality via controllable parameters and to achieve robustness against noises (uncontrollable parameters). This method is iterative: experiments are carried out and numerical results are evaluated iteratively until satisfactory knowledge has been gained. Taguchi design evaluates the quality of a parameter configuration based on crossed orthogonal arrays via a loss function transformation and a measure of the variation or the signal-to-noise ratio. Its aim is to decide the optimal parameters and their levels for the reliable reproduction of the desired characteristic values within a minimal variation range.

The steepest ascent method

In the context of response surface, the response of a process can be described via level changes in process parameters. Interesting practical issues are the combination of an estimation of the surfaces and the identification of near optimal settings of all influential process parameters. An aim is to drive the current operating conditions toward the optimal (or anyway improving) conditions. The actual relationship between the response and the set of process parameters is unknown. A suitable approximation can however be determined via a low-order polynomial—such as a linear function of the first-order model—in some region of the significant (or at least influential) process parameters. Based on the observed data, the appropriate relationship between parameters and quality is modelled via the least-squares technique, and the adjustment quality of the model is assessed using a traditional simple or multiple linear regression tools (Edwards and Fuerte 2011). For k parameters x_i, $i = 1, 2, \ldots, k$, the fitted first-order model for each of R responses is given by

$$\widehat{y}_r = 1\hat{\beta}_0 + \mathbf{X}^T\hat{\beta};\, r = 1, 2, \ldots, R. \tag{1}$$

The path of steepest ascent is then given by $\hat{\beta} = \left[\hat{\beta}_1\hat{\beta}_2 \ldots \hat{\beta}_k\right]^T$ and $\mathbf{X}$ is a vector of $[\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_k]$ and $\mathbf{1}$ is a column of 1's. The $\hat{\beta}$ vector is from the least-squares method and all the x_i are in coded form with the center of the initial design point at $(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_k) = (0, 0, \ldots, 0)$. Such a function describes how the mean response is modified by a change in the process parameters. The process parameters are then optimised using steepest ascent or descent methods on the function. This (heuristically determined) direction is parallel to the normal contour line of the approximated response surface. The sequential experiments are performed along this path until there is no further improvement in the process response, and parameter levels obtained are returned. This algorithm has been widely used to determine the optimal parameters in manufacturing optimisation problems (Hron and Macak 2013; Joyce and Leung 2013; Chen et al. 2014; Zhang et al. 2016). In a system with multiple responses, a considerable tradeoff among the different responses is required. The resulting approach is called compromise steepest ascent

Fig. 1 Pseudo code of the SAM

```
Procedures of SAM()
While (termination criterion not satisfied) - (line 1)
Schedule activities (when second order criteria not satisfied)
   Generate design points from Taguchi orthogonal arrays or factorial designs;
   Evaluate responses of design points;
   Determine the significant first order model from the method of least squares;
   Move along the estimated parameter levels with a step length (Ω);
   If the new one is better than the preceding then
      Move ahead with another Ω;
   Else
      Compute two more design points to verify the descending trend;
      If one of which design points turns out to be better than the preceding then
         Use the best one to continually move along the same path;
      Else
         Use the closest preceding one as a centre for the new design points;
      End if;
   End if;
End schedule activities;
End procedure;
```

method, but this study abbreviated it as SAM throughout. A desirability function is introduced. It is a transformation of the natural responses to desirability values between 0 and 1 via a geometric mean (Harrington 1965). The value 0 represents a completely undesirable response and 1 means the most desirable response. Whilst continually checking the termination criteria such as an evidence of quadratic or interaction effects, the following standard pseudo code describes the steepest ascent method (Fig. 1).

Ant colony system optimisation

Ant colony system (ACS) is a population-based optimisation paradigm based on the imitation of real ants. In more detail, it mimics the natural process for exchanging information between real ants when they look for the shortest route between the nest and a food source (Dorigo and Stutzle 2004). The parallel is therefore between a colony of ants seeking for food and an optimisation process where the aim is to find a (hopefully) global optimal solution according to a given objective function. Ant colony systems have been remarkably successful in solving many difficult discrete combinatorial problems like the traveling salesman, scheduling, network routing, vehicle routing and the quadratic assignment. Many academic problems have been solved successfully by the ant system. A number of companies have realised the value of this algorithm for real-world applications. Later, applications have focused on parameter optimisation problems in industries (Saravanan et al. 2005; Baskar et al. 2005; Mukherjee et al. 2012; Zhang et al. 2005).

In Nature, an ant searching for food prefers to take a direction marked with more pheromone, which is a volatile chemical left on the ground by each ant and can be smelt by all the ants of the same colony. This implies that over time the shortest path between the nest and food tends to have a higher concentration of pheromone, thereby attracting more and more ants, while the pheromone on a non-successful path will gradually evaporate. This process leads to a learning process giving the colony the capability of learning the shortest path. Similarly, in engineering optimisation each decision variable initially selects any value within the feasible region to form a solution vector. If all decision variable values construct a good solution, that experience is stored in a shared memory of pheromone trails, so that future ants will have knowledge on how proficient the parameters were collectively to the selected values. In the long run, the ant colony system will learn how to combine the settings of the individual parameters to obtain better solutions. Additionally, artificial pheromone evaporation is useful to avoid too quick a convergence and to allow artificial ants to better search for alternative regions of the solution space.

The new steepest ant sense algorithm (SASA)

The novel algorithm we propose is a hybridisation of the Taguchi method, the steepest ascent method and the ant colony system. In the product or process development community, there are various engineering applications where process design parameters have to be optimised to achieve desirable (or optimal) combinations of given quality measures. The desirable conditions are usually either a maximum or minimum of the geometric mean of a computed set of desirability indicators d_r, r $= 1, 2, \ldots, R$ where a normalisation $0 \leq d_r \leq 1$ is normally carried out in advance, and for each indicator 1 means optimum and 0 undesirable values. The computation of each desirability indicator d_r works as follows. The target is normally to minimise a predicted measure of error $\hat{Y}_r$. We have a level Y_{r*} near which some product or process is considered nearly flawless, and a value Y_r^* where the product or process is considered unacceptable. A desirability function d_r is then defined as follows:

$$d_r = \begin{cases} 1 & if\ \hat{Y}_r \leq Y_{r*} \\ \left[\frac{Y_r^* - \hat{Y}_r}{Y_r^* - Y_{r*}}\right]^w & if\ Y_{r*} < \hat{Y}_r < Y_r^* \\ 0 & if\ \hat{Y}_r \geq Y_r^* \end{cases} \tag{2}$$

where w is a weighting used to attribute emphasis to various levels of the response. For R responses, the maximal overall desirability (*OD*, the measure that will be optimised) is taken via the geometric mean of the individual desirability, i.e.

$$OD = (d_1 \cdot d_2 \cdot \cdots \cdot d_R)^{1/R} \tag{3}$$

There are two main steps of the proposed Steepest Ant Sense Algorithm, which consist of an exploitation and an exploration phases. The outline of SASA is described in Fig. 2. During an exploitation step, the Taguchi method is first applied to find the design parameters and their levels, determine both orthogonal inner or outer arrays, then designed experiments are collected and experimental results are studied via the analysis of the mean or a signal-to-noise ratio. These sequential procedures are applied to achieve adequate and reliable measurement of the responses of interest. The aim is to concisely determine the influence of design parameters on the overall product or process quality. The influential design parameters identified by the Taguchi method are used to define a first order mathematical model for the response surface. Once such an approximated mathematical model has been built, the steepest ascent path is evaluated for the process response by means of multiple linear regression analysis. The significant terms in the model and the individual regression coefficients are determined via an analysis of variance or ANOVA and T test, respectively. Significance is judged by determining the P value less than a preset significance level (Montgomery 2012). Having fitted the model, the conventional steepest ascent method determines the improvement direction on the hyperplane by changing design parameter levels in proportion to the significant estimated regression coefficients. The next experiment is performed at a design point that is at some fixed distance in that direction. Further iterations of the same method are carried out by continuing on this path of steepest ascent until no further improvement is reported. When the response first deteriorates, an exploration step (explained later) is then carried out to search for the better condition. This phase, and how it is carried out, represents the novelty of the method.

In the exploration step we apply evolutionary elements from the ant colony system paradigm. Before starting the optimisation, we need to set the following parameters: $R+1$, the number of ants and ρ, the evaporation rate, and design parameter domains are discretised. The new design points (combinations of parameter levels) are selected by considering *a posteriori* information given by parameter levels with highest pheromone. The *steepest ant sense algorithm* proposes three alternative exploration modes based on the ant colony system (ACS) which includes iteration best ant system (BAS), best so far ant system (BSFAS) and neighbourhood ant search (NAS). When there is no *OD* improvement from the new points, $R + 1$ design points from the Taguchi's Orthogonal Array are selected and associated with the ants for the first iteration. In the second iteration, solutions associated with ants are from other $R + 1$ design points with the highest *OD* values. Pheromones are then updated. For the ACS, the pheromone τ_{ij}, associated with the j-level of the i-parameter, is updated as follows:

$$\tau_{ij} \leftarrow (1 - \rho) \cdot \tau_{ij} + t_{ij}^{\cdot} \tag{4}$$

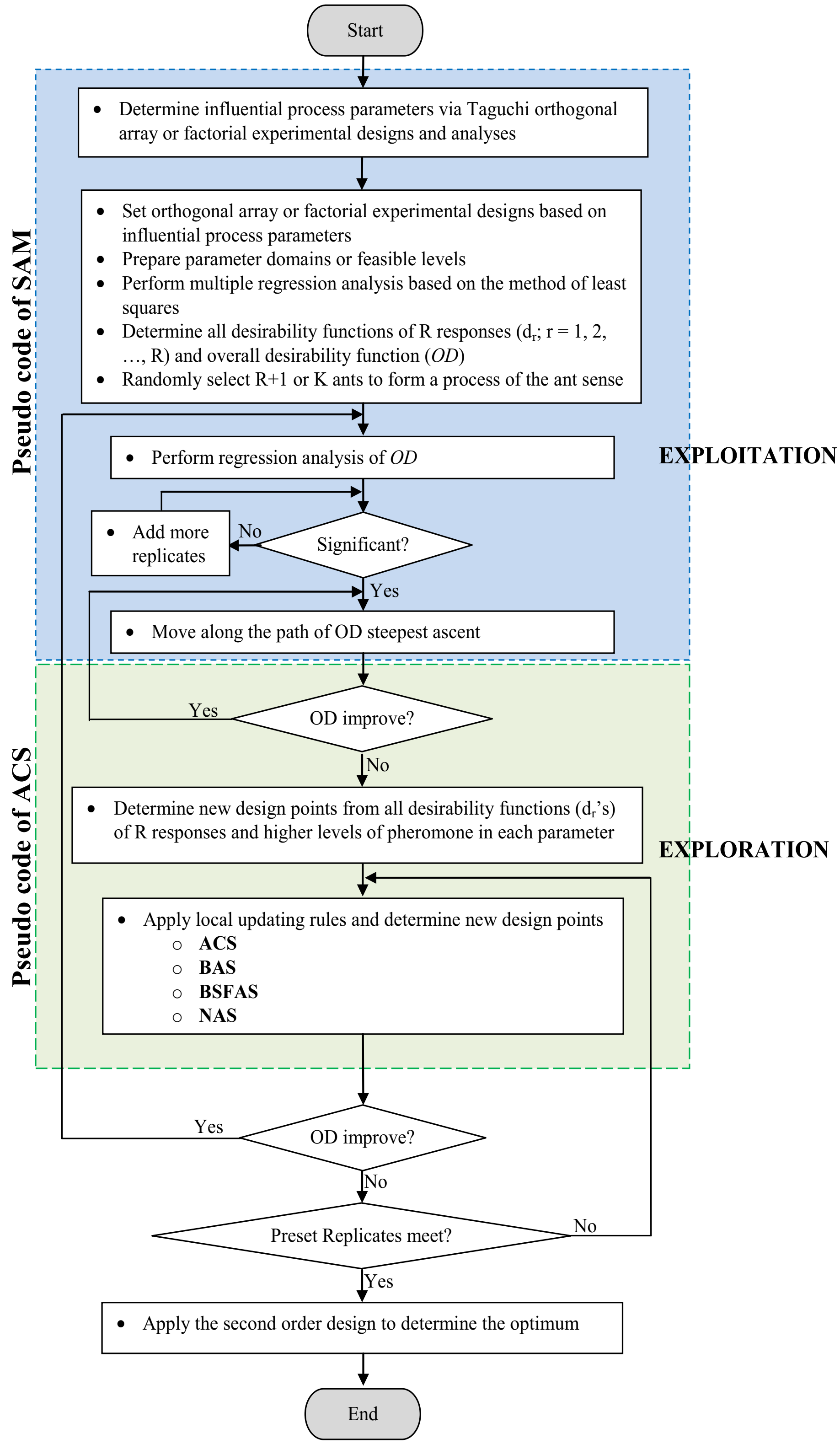
where $t_{ij}^{\cdot}$ is the total pheromone laid on the j-level of the i-parameter after the colony has concluded the computation and is calculated as follows:

$$t_{ij}^{\cdot} = \begin{cases} \sum_{r=1}^{R+1} OD_r & if\ the\ solution\ of\ ant\ r\ used\ the \\ & j-level\ of\ the\ i-parameter\ in \\ & its\ design\ point, \\ 0 & otherwise \end{cases} \tag{5}$$

where OD_r is the overall desirability of the design point constructed by ant r (Fig. 3).

When there is deterioration in yields from both fundamental mechanisms of Taguchi design and steepest ascent method, three variants are then implemented to activate the process toward the optimum. For the BAS, ants select the levels to be visited through a stochastic mechanism based on the best of a preset number of ants to form the new design point. For the BSFAS, the best iteration and additional design points from Taguchi designed orthogonal array are included for ants to form the new design point. In the case of three alternatives or $\left[j - \Delta j \underset{j}{\leftrightarrow} j + \Delta j\right]$, the probability to decrease the parameter level of $(j - \Delta j)$, to maintain the current level (j) and to increase the parameter level of $(j + \Delta j)$ are P1, P0 and P2, respectively or $\left[P1 \underset{P0}{\leftrightarrow} P2\right]$. The probability for an ant to

Fig. 2 Outline of a proposed algorithm: SASA



select any level depends on a random variable uniformly distributed over [0, 1]. Those levels are selected via cumulative probabilities. For example, if the cumulative probabilities for selecting the new levels are [0.25, 0.75, 1] and the random variable assigned to the first ant is 0.67, the first ant then maintains the current level of j as shown in Fig. 4. There are two cases of two possible parameter levels. In the first case of two possible levels or $\left[\overset{j}{\rightarrow}\; j + \Delta j\right]$, the probabilities to

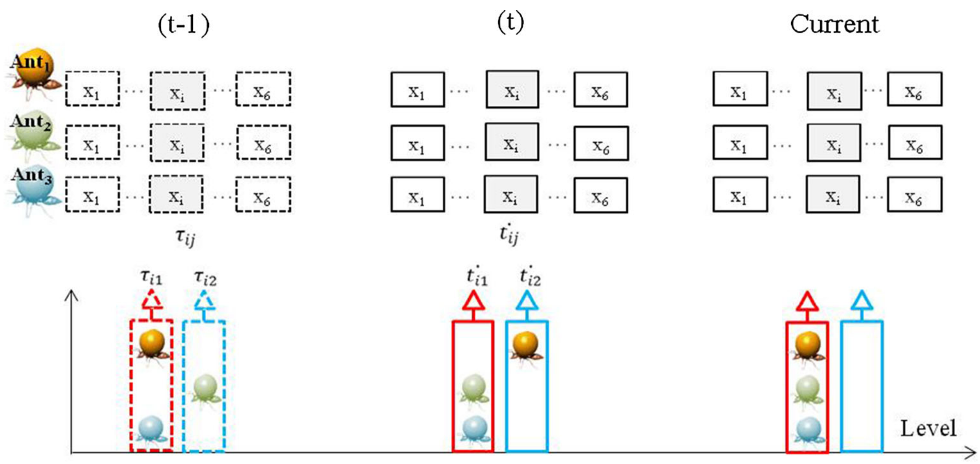


Fig. 3 Presentation of ant pheromone concentration

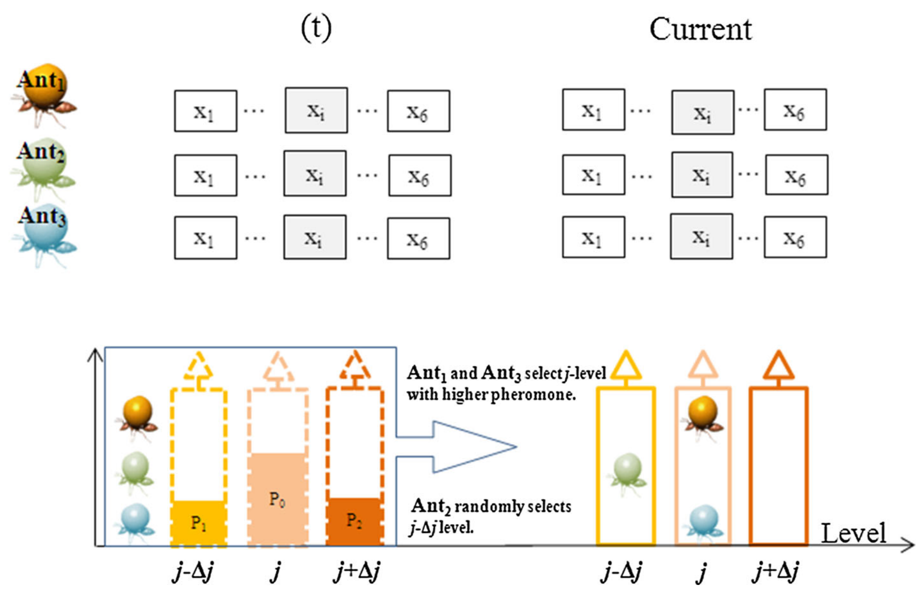


Fig. 4 Presentation of stochastic mechanism based on BAS and BSFAS

maintain the current level (j) and to increase the parameter level ($j+\Delta j$) are P3 and P4, respectively or $\left[\xrightarrow{P3} P4\right]$. In the second one or $\left[j-\Delta j \xleftarrow{j}\right]$, the probabilities to maintain the current level (j) and to decrease the parameter level ($j-\Delta j$) are P5 and P6, respectively or $\left[P6 \xleftarrow{P5}\right]$. Embedding neighbourhood search in the ACS (NAS) is proposed to overcome stagnations, where a solution does not change anymore. The latest solutions are used to check the relationship of the parameter levels against the averaged response or overall desirability (*OD*). The neighbourhood search begins by going through each parameter. In this step, parameter levels and their *OD*'s are considered. If the percentage of an *OD* improvement (ΔOD) from an increase or decrease in parameter levels is larger than a preset value (α), those parameters are adjusted from the current best levels with the level of Δj. During consecutive time periods, if increasing the levels from $j-\Delta j$ to j brings an *OD* increase larger than 5 %, the first ant adjusts to the neighbourhood level of $j+\Delta j$ as shown in Fig. 5. This step is repeated until no further possible change is possible.

In a preliminary study, the evolutionary procedures of the SASA have been tested on various continuous mathematical functions widely used in response surface methodology such as the single peak, the multi-peak and the curved ridges including the multi-peak with curved ridge (Lee and Geem 2005). The confirmation tests on these models based on the predicted operating conditions were verified and carried out to show statistically significant improvement at 95 % confidence interval when compared to two conventional response surface methods of the steepest ascent (SAM) and factorial design (FDM). The numerical experiments were performed on a personal computer under the environment of Intel(R) Core(TM) i5-2410M CPU @ 2.30 GHz and 4 GB of RAM.

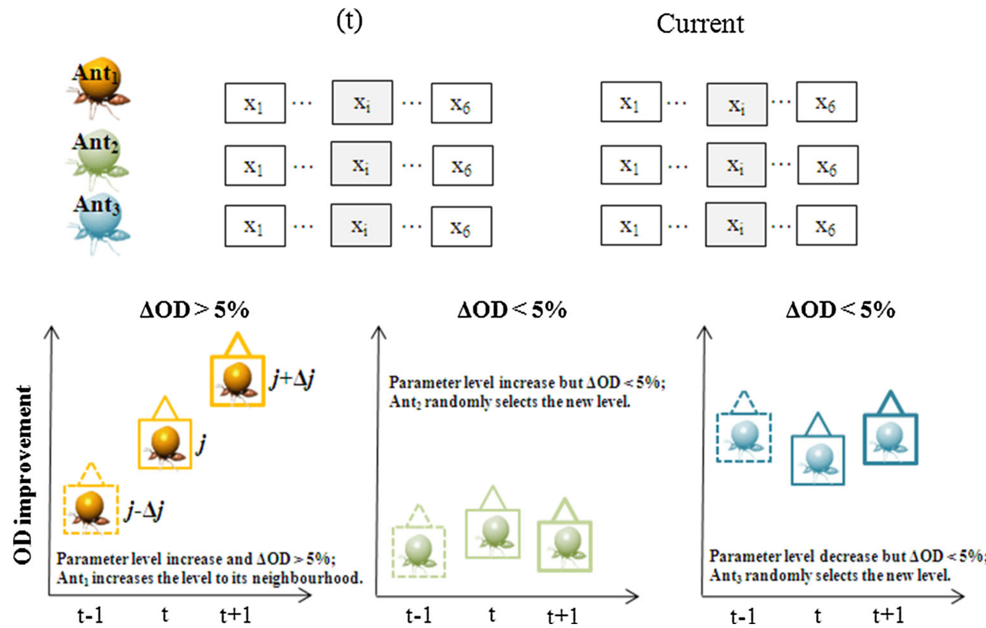


Fig. 5 Presentation of stochastic mechanism based on NAS

Matlab 7.0 package and Visual C#2008 computer program were run to execute the sequential procedures to determine the parameter choices in each case. Each case was experimented 15 times to measure the responses. Theoretical approximations were used to determine the parameter choices. The aim was to optimise the parameter levels and use them as real settings on a stealth laser dicing operation and a grease position tooling process. The sequential procedures of the SASA performed in real experiments followed the steepest ascent method with the replacement of the ant colony system (ACS) procedures (Fig. 6) when there is deterioration in the response or OD during standard procedures (lines 10–15) of the SAM (Fig. 1). The ACS procedures include the iteration best ant system (BAS), the best so far ant system (BSFAS) and the neighbourhood ant search (NAS). These procedures are applied when the new response or desirability value deteriorates or parameter regions are infeasible.

Industrial applications of the SASA and comparison with other methods

Nowadays, there is an increasing competition within the integrated circuit industries in the worldwide market. Integrated circuits (IC) are widely used for different applications. Various factors such as quality, tolerances, delivery times and cost are highly important at production plants. Two case studies from the semiconductor industry were selected to illustrate the proposed integrated approach to multi-response process design. Results of the application of SASA or the integrated intelligent model and the factor effects approach were compared to the results of three popular approaches for multi-response design from the literature. These approaches consisted of factorial design method (Montgomery 2012), Taguchi method (Taguchi et al. 1993) and compromise steepest ascent method (Edwards and Fuerte 2011). Details about the implementation of the general framework to the given applications follow.

Phase 1: Taguchi designs and analyses

In the initial phase, two steps of the Taguchi designed experiments are carried out to determine the consistency of the signal or output characteristics and their noises. The signal-to-noise (S/N) ratio in the Taguchi method was also used to transform quality characteristics for optimising the process. The S/N ratio function depends on the larger the better (L), smaller the better (S) or target the better (T) of the quality characteristics. The following equation (6) of the larger the better (L) was then selected to model such a quantity:

$$S/N_L = -10 \log \left\{ \sum_{i=1}^{n} \left[1/y_i^2\right]/n \right\} \tag{6}$$

From the Taguchi designs and analyses phase, the numerical results are used to determine the influential parameters and the multiple regression for the path of steepest ascent. Some Taguchi design points will later be used within the best so far ant colony system (BSFAS, see “Phase 3: Ant colony system mechanisms” section).

Procedures of ACS()
Begin;
Initialise parameters:
ρ *: an evaporation rate;*
Δj *: a difference of parameter levels;*
α *: a preset value of response or OD improvement;*
Construct R+1feasible solutions;
Determine the response or OD (multiple responses);
Update the best solution;
Global updating rule;
For every combination (i,j)
Find $t_{ij}^{\cdot}$ *according to Eq.(5);*
Update the trail values according to Eq.(4);
End For;
If the response or OD increases then
Go to standard SAM procedures;
Else
Set up the probability to decrease or maintain or increase the current level;
Select the proper level by comparing a random number to cumulative probabilities;
Update the best solution;
If the response or OD increases then
Go to standard SAM procedures;
Else
Determine the percentage of the response or OD improvement;
If the percentage of improvement is larger than α *then*
Adjust the current best levels with the level of Δj*;*
Go to standard SAM procedures;
Else
Generate a new set of ample design points;
Go to standard SAM procedures;
End if;
End if;
End if;
End;
End procedure;

Fig. 6 Pseudo code of the ant colony system (ACS) procedures

Phase 2: Path of steepest ascent

From Taguchi design, the multiple linear regression based on *OD* is determined to form the path of steepest ascent. Sequential experiments are performed along this path until there is no more improvement of the overall desirability (*OD*).

Phase 3: Ant colony system mechanisms

In this phase we apply evolutionary elements from the ant colony system and its variants of BAS, BSFAS and NAS (see "The new steepest ant sense algorithm (SASA)" section). For the first two mechanisms, the best iteration (B) or best so far (BSF) ant selects the levels to be investigated through stochastic mechanisms to form its new design point. For NAS, the probability of the i-parameter of B and BSF used to select the level of $\left[j-\Delta j \underset{j}{\leftrightarrow} j+\Delta j\right]$, $\left[\overset{j}{\rightarrow} j+\Delta j\right]$ or $\left[j-\Delta j \overset{j}{\leftarrow}\right]$ is $\left[0.25 \underset{0.50}{\leftrightarrow} 0.25\right]$, $\left[\overset{0.75}{\rightarrow} 0.25\right]$ or $\left[0.25 \overset{0.75}{\leftarrow}\right]$, respectively. The new level for each parameter is determined via its parameter levels and their $OD\prime$. s of all ants from all iterations. If the percentage of an *OD*. improvement from an increase or decrease in the parameter levels is larger than 5 %, the parameter is set at the new level. For example, in the experiments described in "Experiment 1: Stealth laser dicing process (SLDP)" section, for parameter C it will be possible to have a percentage improvement for OD in the order of 9.201 % from an increase in the parameter levels from 0.36 to 0.38 ($\Delta j = 0.2$). Since this was larger than 5 %, the following setting of C to test was selected at 0.40.

Experiment 1: Stealth laser dicing process (SLDP)

The production process for a die was analysed with the aim of providing optimised production parameters to reduce the average and standard deviation of some representative feature of the products with respect to the expected one (tolerance) and thus to guarantee a significant increase in the number of dies per wafer with efects. We focused on the stealth laser dicing process, a high-quality dicing technology where a laser is applied by internal processing to cut a semiconductor wafer into small dies. Such a technology provides high accuracy and high production speed at a low cost. A laser diode generates a pulse to break the wafer into dies with no chip or crack. Such a technology is quite new, so process parameter tuning is still an open issue. If the production tolerance is too high, pieces might be defective and look like wavy kerf (Kumagai et al. 2007). In semiconductor fabrication, there are two types of dicing processes that consist of mechanical sawing and laser cutting. Both operate automatically to ensure the precision and accuracy. The innovative and high capability concept to separate dies from a wafer is stealth laser dicing. An interesting feature of the SLDP is the high-speed process without chipping, no frictional heat or debris contamination and a completely dry process. Therefore, this process does not require any cleaning sub procedure with water or other fluids. In this dicing process, a laser-based technique is used to dice silicon wafers on the saw lane to dies without causing defects such as cracking on the wafer. Its performance can support the silicon wafer within the required target of a saw lane width. During the SLDP, semiconductor wafers are typically mounted on a back grinding tape which holds the wafer on a thin frame. A laser diode is used to generate the pulse to destroy the silicon structure. The laser beam at a wavelength permeable to a semiconductor wafer is scanned along intended dicing lines. An underlying carrier membrane only occurs on the interior of the wafer to induce fracture (Fig. 7).

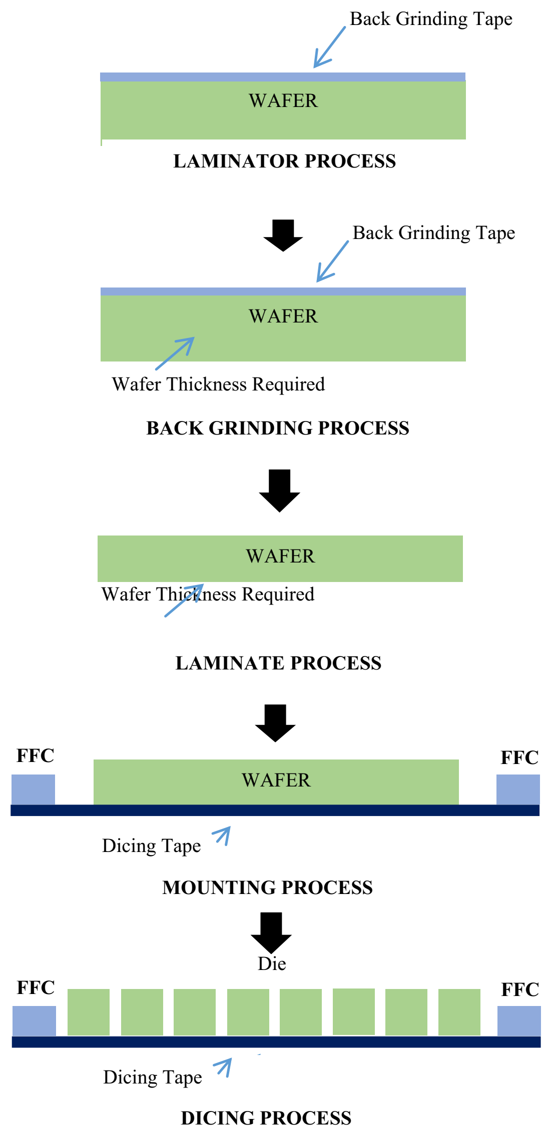


Fig. 7 Stealth laser dicing process (SLDP)

In the SLDP, the current level of meandering (Fig. 8) on SLDP layers along the scanned line in the wafer is the main problem. The meandering measures of both the central tendency and the standard deviation are slightly higher than the customer specification (Fig. 9). This situation leads to quality inspection of a large sample size with high frequency. This results in a higher production cost and also wastes time and labor. Therefore, a meandering quality measures in the SLDP need to be improved. Since the collaboration with the Thai Company carrying out the production was based on a no-disclosure agreement, all the data reported in the remainder of the paper have been modified (in such a way that the readability of the results is not compromised).

In a preliminary study, a two level experimental design was performed to determine the statistical significance of five process parameters, which were the scanning height (A), scanning power # 1 (B), scanning power # 2 (C), beam shape (D) and scanning speed (E). The feasible ranges, the current operating condition and their possible differences of operation (Δ) are provided in Table 1 (all are coded levels). The problem of interest was the drift of meandering data in the stealth laser dicing process. The current mean and standard deviation of meandering were at -3.2 and 314.5, respectively. The A-process parameter is a combination of (First, Second) scanning height of a laser (Fig. 10) for this SLDP. The following seven combinations are possible, and define A levels: (10, 9), (11, 8), (12, 7), (13, 6), (14, 5), (15, 4) and (16, 3). These combinations are coded by the approach into 1, 2, 3, 4, 5, 6 and 7, respectively. The feasible levels of beam shape (D) consist of ultrathin (1), thin (2) and thick (3). The meandering data is then measured and compared with the customer specification. The mean target is -19.0 microns and the standard deviation target is 232.0.

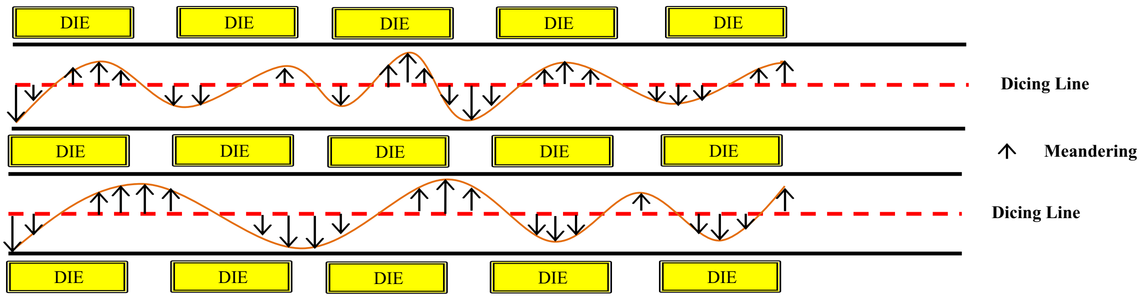


Fig. 8 Meandering

Fig. 9 2014–2015 Actual operating performances

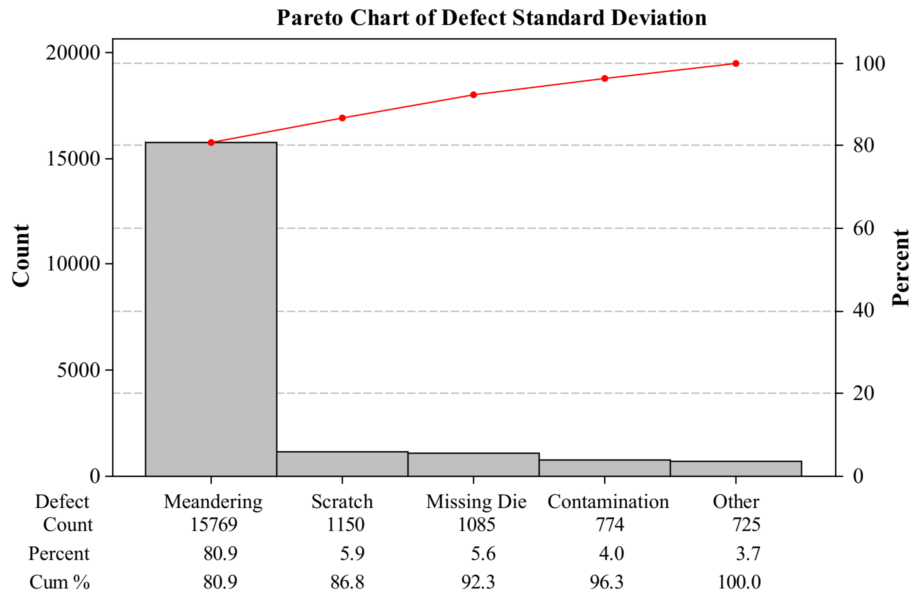


Table 1 Process parameters, feasible ranges and the current operating condition

Process parameter	Feasible range		Current	Δ
	Lower	Upper		
A	1	7	4	1
B	0.12	0.48	0.24	0.01
C	0.18	0.72	0.36	0.01
D	1	3	1	1
E	100	300	200	10

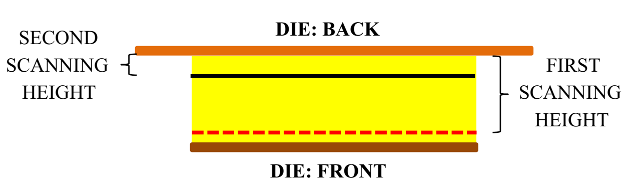


Fig. 10 (First, second) laser scanning height

The controllable parameters A, B, C, D and E were selected to estimate effects on the performance indicators of the mean and standard deviation of meandering. This paper investigates how the proposed SASA based on ACS stochastic evolutionary elements may be applied to the challenging industrial problem of finding the optimal operating condition. The standard L8 orthogonal array was employed to design these experiments. A minimal number of experimental runs could be effectively employed to determine the influential effects of these parameters. The experiments were kept within the actual stealth laser dicing process specifics, provided by the Company. The qualitative evaluations of some selected process parameter levels combinations were made from the previous data set by the decision maker (DM). The experiments highlighted some interaction effects between process parameters. Notably, A–B and B–C interactions were identified. The (lower, higher) or (1, 2) levels of the process parameters of A, B, C, D and E were (4, 5), (0.24, 0.26), (0.36, 0.38), (1, 2) and (200, 210), respectively. With three replicates for each combination and with the help of the DM, each natural response (r) from experimental results was transformed into its individual desirability (d_r). An overall desirability (OD) was also determined by using the attribute weighting (w) of one. The (lower, upper) bounds of the mean and standard deviation were (−15, 0) and (300, 350), respectively.

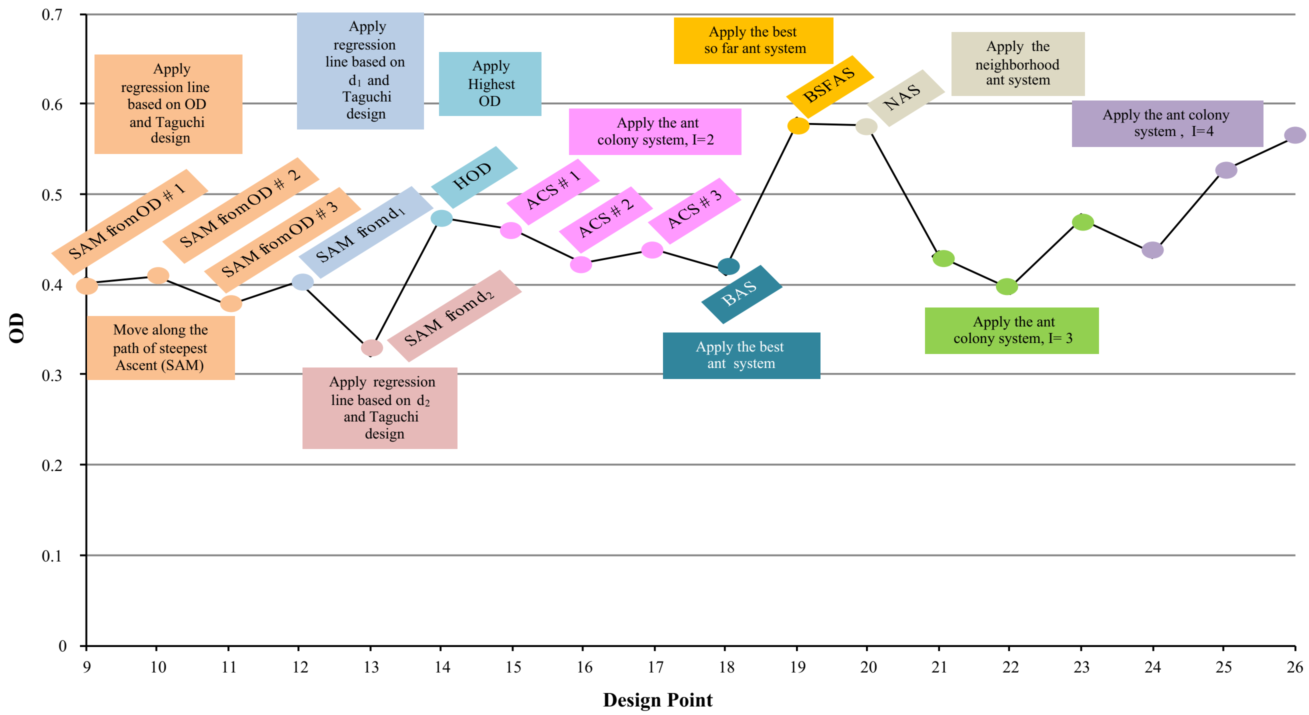


Fig. 11 SLDP: evolution of the overall desirability for different design points

Table 2 Influential Effects on the OD and S/N of OD

Rank	A	B	AB	C	D	BC	E
OD	5	3	1	4	7	6	2
S/N of OD	4	2	1	5	6	7	3

Levels of significance and importance were determined for the process parameters by analysis of variance (ANOVA). The results for Taguchi design, multiple regression and ant system are summarised in Fig. 11.

The numerical results of the influential effects based on the yield differences and the main effect plots were categorised by the desirability types of OD (Table 2), d_1 (mean) and d_2 (standard deviation). When compromising both responses, influential parameters were A, B, C and E. The lower A levels led to desirable mean of meandering levels. In contrast, parameters A and C highly affected the standard deviation of meandering and lower levels on both parameters brought undesirable standard deviation. In the first phase, the analyses were categorised by the desirability types of OD, d_1 and d_2. When compromising both responses, influential parameters were A, B and E. However, the A levels had the most important effect. Their lower levels led to the desirable standard deviation and provided thrable mean of meandering levels. These conflicting effects were repeated on the C parameter in the opposing way. From Taguchi analyses based on OD, the influential process parameters were A, B, C and E. The influential process parameter affecting the mean of responses (d_1) could be A, and the influential process parameters affecting the standard deviation of responses (d_2) could be A and C. The multiple regression line based on OD and its influential process parameters wasmined via the method of least squares. However, the coefficient corresponding to the C parameter was proven not statistically significant (Table 3). This regression line was used as the subprocedure of the path of steepest ascent to achieve the higher levels of overall desirability (OD). The additional procedures based on Taguchi method were carried out to determine the regression lines of the desirability function of the mean (d_1) and the standard deviation (d_2) of meandeng values (Table 4). There were some moves along the path until there was no OD increase, at the design point (DP) # 11. Instead of applying the conventional second order design, new design points were determined via the multiple linear regression based on d_1 (DP# 12) and d_2(DP# 13) and the highest OD (HOD) from all Taguchi design points (DP# 14).

The novel SASA procedure we propose was then applied to try to exit from a local optimum. Three different design points (ants) were randomly selected from all 11 design points to be three ants for the first iteration (I = 1). Another three design points were also picked from d_1, d_2 and HOD, to be ants for the second iteration (I = 2). The new ants or DP# 15, 16 and 17 for the third iteration were generated via the ant system mechanisms by equation (10). Some design points were investigated by applying local updating rules of BAS

Table 3 Regression Coefficients and the Analysis of Variance of the Model based on OD

Predictor	Coeff	SE Coeff	T	P value	
Constant	0.15575	0.05387	2.89	0.015	
A	0.01525	0.01771	0.86	0.408	
B	0.04475	0.01771	2.53	0.028	
C	−0.02200	0.01771	−1.24	0.240	
E	0.04550	0.01771	2.57	0.026	
Analysis of Variance					
Source	DF	SS	MS	F	P value
Regression	4	0.019157	0.004789	3.82	0.035
Residual error	11	0.013803	0.001255		
Total	15	0.032960			

Table 4 Summarisation of Regression Coefficients and the Analysis of Variance of the Model based on Individual Desirability Function

Function	$\widehat{d_1}$		$\widehat{d_2}$		
Predictor	Constant	A	Constant	A	C
Coeff	−0.1745	0.35738	0.92500	−0.26800	−0.14375
SE Coeff	0.1224	0.07739	0.02950	0.01353	0.01353
T	−1.43	4.62	31.36	−19.80	−10.62
P value	0.176	0.000	0.000	0.000	0.000
F: ANOVA	21.32		252.45		
P value: ANOVA	0.000		0.000		

to *DP*#18, BSFAS to *DP*#19 and the neighbourhood search or NAS to *DP*# 20. *DP*# 18 and 19 were determined by their parameter levels from the best iteration or B (this case from ACS) and the best so far or BSF (this case from Taguchi), respectively. However, at this moment the levels were very similar, and in fact corresponded to the same design point. For *DP*# 20, this ant used the neighbourhood search or NAS. The *OD* was then improved when C level increased from 0.36 to 0.38 or with the positive difference of 0.2. The DM decided to increase the C level to 0.4. These mechanisms from ant colony system seemed to be good alternatives to the existing algorithm for seeking the parameter settings of the SLDP. The novel algorithm showed its performance to avoid getting stuck at the local optimum instead of using the second order based methods when compared to the traditional response surface algorithms.

Various hybridisations based on the ant system were carried out to improve the search efficiency of the compromise steepest ascent method (SAM). By integrating the previous design points from Taguchi array and the SAM, solution-finding was diverse to avoid settling at a local optimum and achieve better operating condition. Regarding the initialisation process of the ACS, the first step was to determine the initial ants or design points. To avoid a biased exploration, different random initial configurations were performed with the same local and global pheromone updating rules. However, from experimental results of *DP*# 21, 22 and 23 (Fig. 11); there was no difference in the overall search efficiency of the ACS. In the fourth iteration of the proposed algorithm it might be that a series of the overall desirability did not improve. The decision maker could systematically adjust the preference parameters of shape, bound, or target of the desirability function by using the tradeoffs information.

In conclusion, the optimised controllable parameters of the scanning height (A), scanning power # 1 (B), scanning power # 2 (C), beam shape (D) and scanning speed (E) were 5, 0.25, 0.39, 1 and 220, respectively. Performances of the desirability of the mean and the overall desirability level (*OD*) have been simultaneously improved by 159.4774 and 49.4049 %, respectively. There was a low decrease (13.9694 %) in the desirability of the standard deviation. This process optimisation was provided by the steepest ascent method. These experimental results demonstrated that the ant colony system mechanisms were efficient and greatly enhanced both performance measures on meandering data.

Although a parameter optimisation procedure is a valuable technique for various application domains, conventional techniques based on experimental designs and analyses are still widely used in the Industry. For comparison purposes, we report the results we have obtained with Taguchi method (TM), compromise steepest ascent method (SAM) and fac-

Table 5 Comparison of different optimisation methods on the SLDP

Method	Parameters					Sample mean		
	A	B	C	D	E	$\widehat{d}_1$	$\widehat{d}_2$	$\widehat{OD}$
FDM	4	0.24	0.36	1	200	0.214	0.708	0.389
TM	5	0.26	0.38	1	210	0.366	0.621	0.477
SAM	4	0.27	0.35	1	210	0.229	0.726	0.408
SASA	5	0.25	0.39	1	220	0.552	0.607	0.579

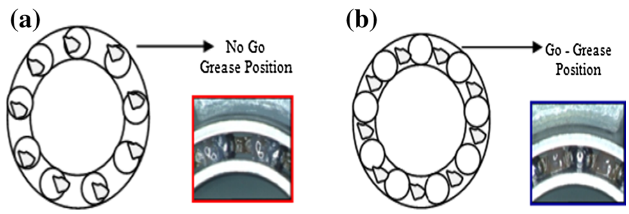


Fig. 12 Bearing with no-go (**a**) and go (**b**) grease positions

torial design method (FDM). The comparison of results of the SASA with other selected methods are summarised in Table 5. From the overall desirability function there is statistical evidence that the mean values of the SASA provide the preferable operating conditions when compared. This new parameter tuning via the SASA has been adopted by the company.

Experiment 2: Grease filling system (GFS)

In electronic industries, grease is important for the bearings in component machining tools. Benefits of grease are to increase compactness of metal ball and to minimise wear under high load conditions. It improves operation reliability for bearings at high speeds, high load capacities and greater energy savings. However, grease leakages during a filling process bring a lot of failed parts with wrongly positioned filling or grease no-go parts (Fig. 12). In this case study, this uncontrollable situation affects the purchasing department of unit grease supplies. Additionally, the producer must be careful to save resources, conserve energy and decrease wasted grease to care for the environment. Therefore, a system for greasing bearings to be maintenance free for a long life was developed and evaluated. However, it is impractical to determine directly the greasing position with sufficient accuracy. For mass production a new grease filling system with twin (left, right) towers contributes to increase the precision of operations, leading to higher productivity, higher speed and greater reliability (Fig. 13). However, the new system brought a new problem concerning the difficulty of controlling grease filling system parameters. At current operating conditions, the tooling life times or time until achieving grease no-go parts on both left and right towers are 9236 U on average.

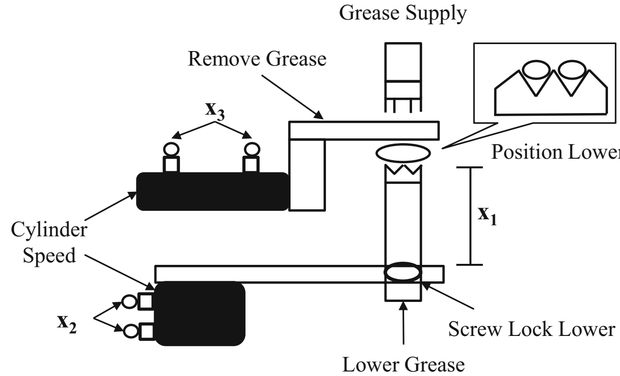


Fig. 13 Side view of the grease filling system

An experiment was conducted to optimise the grease filling system in bearing assembly. Six process parameters were studied within the feasible lower and upper ranges: lower grease supply distance (mm):78 and 82; lower grease supply speed (kgf/cm^2): 4.3 and 5; removal pressure speed (kgf/cm^2): 3.8 and 4.7; protection equipment height (mm): 1 and 2; cycle time (second): 2.0 and 2.1; pallet lock speed (kgf/cm^2): 3.9 and 4.6. The quality of the considered system is determined by the number of parts filled with grease before the inspection department detects a grease no-go part. The tooling life times determined via the twin grease filling system on the left (yL) and the right (yR) towers were considered as the first and the second response. Both responses are variables of the larger the better type. To solve this problem, the parameter settings of the grease filling system (GFS) should be maximised.

The same procedure described in "Experiment 1: Stealth laser dicing process (SLDP)" section for the SLDP was employed here. By using Taguchi experimental plan, the orthogonal array was generated. Since there were six controllable parameters varied on two levels without noise, the plan presented a standard L8 (2^7) orthogonal array with eight treatments and the maximum number of factors for screening up to seven. After performing experimental trials, both responses were measured for two replicates. By analysing the observed data, the effective parameters having an influence on the tooling life times and their desirability function levels (dL and dR) including overall desirability (OD) could be seen and the preferred levels of the process parameters could be obtained. Based on the average values, analysis of means (ANOM) diagrams were drawn indicating the parameter impact of lower grease supply distance (x_1) and lower grease supply speed (x_2) based on the performance measures of OD and dR. Parameters of lower grease supply distance (x_1), cycle time (x_5) and pallet lock speed (x_6) affected dL as shown in the table below.

When the current region of experimentation is assumed to be far from the optimum—like in this case—a first-

Table 6 Ranks of parameters categorised by desirability functions

Functions	Parameter and interaction						
	x_1	x_2	x_1x_2	x_3	x_4	x_5	x_6
OD	1	2	3	5	6	4	7
dL	1	7	6	4	5	2	3
dR	1	2	3	4	7	5	6

order approximated function to the response surface is often conducted. A steepest ascent method will rapidly locate an improved response design point. From the experimental design and the results in Table 6—with the statistically significant level set at 10 %—four parameters of lower grease supply distance (x_1), lower grease supply speed (x_2), cycle time (x_5) and pallet lock speed (x_6) were investigated in an experiment involving the grease filling system to determine their effects on three responses of overall desirability function (OD), desirability function of tooling life time on the left (dL) and the right (dR) towers. All responses were to be maximised. The first-order response functions representing OD and dR could be expressed as a function of two significant parameters, namely lower grease supply distance (x_1) and lower grease supply speed (x_2). Only parameter of lower grease supply distance (x_1) significantly affected dL (Table 7). There were lack-of-fit tests indicating no presence of pure quadratic curvature in each of these simple models. The relationships between the responses and influential parameters to determine the direction of rapid improvement for each response were obtained as follows:

$$\widehat{\mathrm{OD}} = 9.402 - 0.08877x_1 - 0.3911x_2$$
$$\widehat{\mathrm{dL}} = 3.89 - 0.0403x_1$$
$$\widehat{\mathrm{dR}} = 11.215 - 0.1038x_1 - 0.5468x_2$$

Based on the fitted models, the steepest ascent direction for $\widehat{OD}$ was determined to find the required direction of changing parameters by decreasing the lower grease supply distance (x_1) and lower grease supply speed (x_2) to improve the overall desirability. The results from the steepest ascent path indicated that the yield profile had a maximum at the design point (*DP*) # 9 and got worse at *DP#* 10. Artificial ants randomly constructed R solutions, a finite set of available design points from the OA and the path of steepest ascent. In this case, on the first iteration they consisted of *DP#* 3, 4 and 5. Each ant represented a solution string, with a selected level (j) for the ith influential parameter. The newly determined ants of *DP#* 11, 12 and 13 formed via the path of steepest ascent on dL and dR included the ant with the highest level of OD (HOD) based on Taguchi design points, respectively. Accordingly, pheromone concentration associated with each possible route (parameter level) was changed in a way to reinforce good solutions. The concentration of pheromone at the previous iteration with pheromone evaporation rate of 0.4 brought new ants of *DP#* 14, 15 and 16, but *DP#* 14 was similar to *DP#* 15. Additionally, the best iteration (B) or best so far (BSF) ant selected the levels to be visited through stochastic mechanisms to form its new design point. The probability levels of P1, P2, P4 and P6 from the current best or the best so far were set at 0.25 throughout. Moreover, there was embedding neighbourhood search in the ACS (NAS). If the percentage of an *OD* improvement from an increase or decrease in parameter levels was larger than 5 %, those parameters were adjusted from the current best levels with the level of Δj.

Applying BAS, BSFAS and NAS got new ants of *DP#* 17, 18 and 19, respectively. After updating ACS for two cycles the best so far condition was *DP#* 23 via BAS. Parameters of lower grease supply distance (x_1), lower grease supply speed (x_2), removal pressure speed (x_3), protection equipment height (x_4), cycle time (x_5) and pallet lock speed (x_6) were 79.5, 4.8, 4.6, 1, 2 and 4.5, respectively. The evolution of the design points is shown in Fig. 14. The tooling life time responses were at 14,805.99044 and 12,960.14307 U for the left and right towers of the GFS. The results of the SASA were compared with results of FDM, TM and SAM as shown in Table 8. Quantitative comparisons between the experimental results of SASA and those of the other three methods reveal that the new set of GFS parameters obtained through the series of sequential procedures proposed in this research provided reliable results.

The numerical results on SASA resulted in a better overall desirability function. At the new operating condition, the mean time between failures or the mean time until there is

Table 7 ANOVA for regression models and related coefficients

$\widehat{\mathrm{OD}}$			$\widehat{\mathrm{dL}}$			$\widehat{\mathrm{dR}}$		
Parameter	$\hat{\beta}$	P value	Parameter	$\hat{\beta}$	P value	Parameter	$\hat{\beta}$	P value
Constant	9.402	0.000	Constant	5.248	0.010	Constant	11.215	0.000
x_1	−0.08877	0.001	x_1	−0.0403	0.051	x_1	−0.1038	0.001
x_2	−0.3911	0.018	x_5	−0.4796	0.221	x_2	−0.5468	0.007
			x_6	−0.0872	0.264			

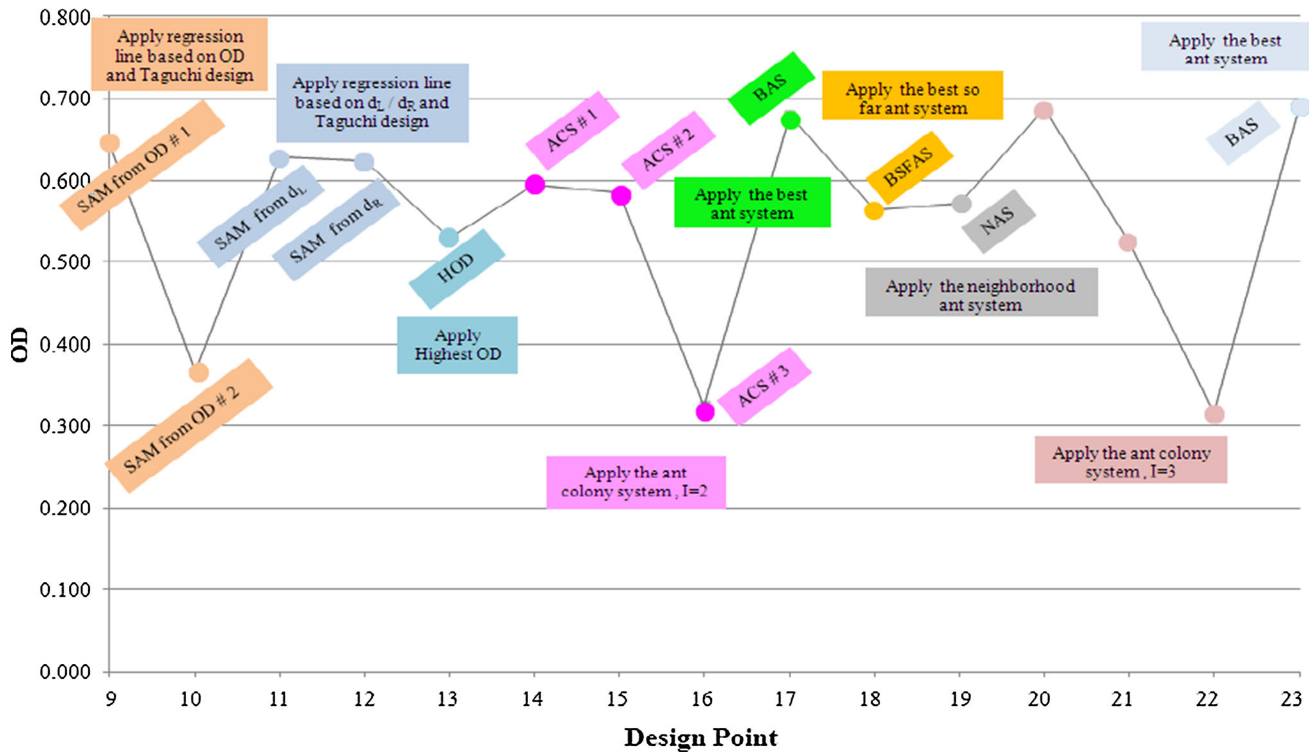


Fig. 14 GFS: evolution of the overall desirability for different design points

a grease no-go part was 13,883 U on average while the previous average was 9236 U. The benefits from adopting the new decision technology of the SASA, as in the GFS example, are that the Company can predetermine when the twin grease filling system should be replaced and achieve longer tooling life times. However, there are learning costs typically incurred at the time of adoption for using some types of new technology. It is typically much less than the cost to the purchasing department when timing of grease supplies are unpredictable and result in higher inventory.

Normally, the actual data sets are assumed to be used during a reported process optimisation. However, in this paper, the actual data we used at the factories were concealed and their domain was shifted as was done for the first experiment (stealth laser dicing) to keep the mercantile secrets. The goal is to gain benefits from applying these sequential procedures on other learning machines.

Table 8 Comparison of different optimisation methods on the GFS

Method	Parameters						Sample mean		
	x_1	x_2	x_3	x_4	x_5	x_6	$\widehat{dL}$	$\widehat{dR}$	$\widehat{OD}$
FDM	82	4.8	4.5	1	2	4.5	0.670	0.221	0.385
TM	80	4.5	4	1	2	4	0.668	0.485	0.570
SAM	82	4.7	4	1	2	4	0.634	0.657	0.645
SASA	79.5	4.8	4.6	1	2	4.5	0.740	0.648	0.693

Conclusions

We have proposed a novel methodology to optimise the control parameters of typical industrial processes. The SASA is based on the combination of the conventional Taguchi designs, steepest ascent and ant colony systems. Principal advantages of this combination of SASA are high accuracy, reliability, efficiency and confidence with a lower number of design points while searching the optimum. The SASA has been applied to a specific stealth laser dicing process (SLDP) and a grease filling system (GFS) in a Thai electronics factory producing integrated circuits. The results obtained showed that the new method was effective in improving the settings and in turn the production quality. This procedure showed effectiveness, efficiency and accuracy in noisy scenarios and allowed for the proper identification of parameter settings in the SLDP and the GFS studied, whereas for the conventional response surface methods, the low confidence and reliability of overall desirability levels make their use unsuitable for these problems. The SASA demonstrates an excellent tradeo? between exploitation of the steepest ascent method and exploration in ant colony systems. Based on overall desirability, the high confidence and stability of the

SASA combined with its simple computation structure could lead to solving real-life and real-time manufacturing optimisation problems in industry. The promising and viable hybrid method can be applied to determine the appropriate operating conditions for any process parameter calibration problem, (very common in the production industry), in order to achieve desired quality characteristics. Future investigations will look for new integrated methods to compare with the ant system on the steepest ascent method to enhance its performance as indicated in this work. Better convergence effects could be achieved for solving multi-response surface problems. These methods aim to improve local search ability, thus enhancing the effectiveness of searching for a global optimum.

Acknowledgements This work was supported by the National Research University Project of Thailand Office of Higher Education Commission. The first author wishes to thank the Faculty of Engineering, Thammasat University, THAILAND.

References

Baskar, N., Asokan, P., & Prabhaharan, G. (2005). Optimisation of machining parameters for milling operations using non-conventional methods. *The International Journal of Advanced Manufacturing Technology*, *25*(11), 1078–1088.

Chen, H., Zhang, J., Dang, Y., & Shu, G. (2014). Optimisation for immobilisation of β-galactosidase using plackettburman design and steepest ascent method. *Journal of Chemical and Pharmaceutical Research*, *6*(4), 612–616.

Çiçek, A., Kıvak, T., & Ekici, E. (2015). Optimisation of drilling parameters using Taguchi technique and response surface methodology (RSM) in drilling of AISI 304 steel with cryogenically treated HSS drills. *Journal of Intelligent Manufacturing*, *26*(2), 295–305.

Dorigo, M., & Stutzle, T. (2004). *Ant colony optimisation*. Massachusetts: The MIT Press Cambridge.

Edwards, D. J., & Fuerte, J. N. (2011). Compromise ascent directions for multiple-response applications. *Quality and Reliability Engineering International*, *27*(8), 1107–1118.

Harrington, E, Jr. (1965). The desirability function. *Industrial Quality Control*, *21*, 494–498.

Hron, J., & Macak, T. (2013). Optimisation of food packaging to improve food safety. *Journal of Food, Agriculture and Environment*, *11*(3–4), 423–428.

Joyce, A. P., & Leung, S. S. (2013). Use of response surface methods and path of steepest ascent to optimise ligand-binding assay sensitivity. *Journal of Immunological Methods*, *392*, 12–23.

Kuo, C. F. J., Lan, W. L., Chang, Y. C., & Lin, K. W. (2016). The preparation of organic light-emitting diode encapsulation barrier layer by low-temperature plasma-enhanced chemical vapor deposition: a study on the SiO x N y film parameter optimisation. *Journal of Intelligent Manufacturing*, *27*(3), 581–593.

Kumagai, M., Uchiyama, N., Ohmura, E., Sugiura, R., Atsumi, K., & Fukumitsu, K. (2007). Advanced dicing technology for semiconductor wafer-stealth dicing. *IEEE Transactions on Semiconductor Manufacturing*, *20*(3), 259–265.

Lee, K. S., & Geem, Z. W. (2005). A new meta-heuristic algorithm for continuous engineering optimisation: harmony search theory and practice. *Computer Methods in Applied Mechanics and Engineering*, *194*, 3902–3933.

Lin, W. T., Tsao, L. C., Shie, A. J., Chang, S. T., & Yang, T. C. (2016). The application of Taguchi methods to parameters optimisation for preventing coagulation in artificial kidneys. *Journal of Industrial and Production Engineering*, *33*(4), 247–252.

Montgomery, D. C. (2012). *Design and analysis of experiments*. New York: Wiley.

Mukherjee, R., Chakraborty, S., & Samanta, S. (2012). Selection of wire electrical discharge machining process parameters using non-traditional optimisation algorithms. *Applied Soft Computing*, *12*, 2506–2516.

Myers, R. H., Montgomery, D. C., & Anderson-Cook, C. M. (2016). *Response surface methodology: process and product optimisation using designed experiments*. New York: Wiley.

Saravanan, R., Sankar, R. S., Asokan, P., Vijayakumar, K., & Prabhaharan, G. (2005). Optimisation of cutting conditions during continuous finished profile machining using non-traditional techniques. *The International Journal of Advanced Manufacturing Technology*, *26*(1), 30–40.

Sibalija, T. V., & Majstorovic, V. D. (2012). An integrated approach to optimise parameter design of multi-response processes based on Taguchi method and artificial intelligence. *Journal of Intelligent Manufacturing*, *23*(5), 1511–1528.

Taguchi, G., Yokoyama, Y., & WU, Y. (1993). *Taguchi methods—Design of experiments*. Dearborn, Michigan: ASI Press.

Zhang, B., Chen, D., & Zhao, W. (2005). Iterative ant-colony algorithm and its application to dynamic optimisation of chemical process. *Computers & Chemical Engineering*, *29*(10), 2078–2086.

Zhang, J., Sun, H., Pan, C., Fan, Y., & Hou, H. (2016). Optimisation of process parameters for directly converting raw corn stalk to biohydrogen by clostridium sp. FZ11 without substrate pretreatment. *Energy and Fuels*, *30*(1), 311–317.

Zirehpour, A., Rahimpour, A., Jahanshahi, M., & Peyravi, M. (2014). Mixed matrix membrane application for olive oil wastewater treatment: Process optimisation based on Taguchi design method. *Journal of Environmental Management*, *132*, 113–120.