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Metal Removal Process Optimisation using Taguchi Method - Simplex Algorithm (TM - SA) with Case Study Applications

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Abstract: In the metal removal process industry, the current practice to optimise cutting parameters adopts a conventional method. It is based on trial and error, in which the machine operator uses experience, coupled with handbook guidelines to determine optimal parametric values of choice. This method is not accurate, is time-consuming and costly. Therefore, there is a need for a method that is scientific, cost-effective and precise. Keeping this in mind, a different direction for process optimisation is taken by employing the combined Taguchi method-simplex algorithm (TM-SA) for optimal parametric setting of manufacturing processes. The process parameters were optimised and the efficiency and robustness of the method described in four literature cases. These cases involve high-speed flat-end milling, forming in hydrodynamic deep drawing, cup deep drawing and abrasive assisted drilling. The computations showed that the TM-SA exhibited superior results in one of the cases and equivalent results in others. This implies that the proposed approach could comparably serve as an optimisation framework with significant advantages of reducing experimental costs and allowing variable usages with the requirement of functional derivation. It is also easy to use. The novelty of this article is the application of a distinctly new method in optimisation for cost reduction and variable usages for the metal removal process. Potential applications of the proposed approach by material type is its usage in machining mild steel, grey cast iron, brass and aluminium with HSS and carbon steel, respectively, used as tools.

Keywords: Optimisation, parameters, Taguchi method, simplex algorithm, metal removal process.

1. Introduction

Nowadays, it is common to observe that many manufacturing processes such as metal removal [1,2] face huge problems including over-production of defective products, unnecessary transportation during parts processing, waiting to receive instructions from superiors on

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actions to take. Others may be inventory build-up, over-processing of parts and under-utilisation of labour. The metal removal process is a popular one in manufacturing industries with many applications in mechanical and chemical systems. Turning, milling, drilling, broaching, hoving and sawing are the major examples of mechanical metal removal processes. In addition, chemical machining, thermal, touch-cutting and electric discharge machining are significant processes in chemical metal removal. The major aim of many metal removal processes is to remove metals as quickly as possible with bias for low production time and production cost [3]. Generally, in the metal removal process industry, a number of indices are used to evaluate the performance of the process and hence many processes are referred to as multi-performance based. For example, [3] identified two indices for a high-speed end milling process as tool life and metal removal rate. These two indices were correlated with cutting parameters, including milling type, spindle speed fed per tooth, radial depth-of-cut and axial depth-of-cut. Thus, these types of performance problems exist in mechanical and chemical metal removal processes.

At present, in industries, operator's experience is used in determining the optimal values of the parameters involved in the metal removal process. This experience is often coupled with handbook values provided by machine manufacturers. Unfortunately, such practices are subjected to errors and there is no guarantee that the values obtained from such practices are near optimal results. As a consequence, it is important to find out simple and effective optimisation methods that could serve the purpose of a fast evaluation of metal removal process parameters. A metal removal optimisation problem refers to one which requires the objective function to either be minimised or maximised in conjunction with a set of constraints. Thus, in this paper, the authors take a different direction for process optimisation by applying a combined Taguchi method-simplex algorithm (TM-SA) for the optimal parameter setting of a manufacturing process. The details of the method used with four case examples are provided.

In the domain of metal removal process parametric optimisation, the central theme has been the use of the Taguchi method (TM). However, with the growing interest of optimisation as a competitive tool towards sustained manufacturing [4,5,6], it is evident that the problem of obtaining improved optimisation results must be addressed urgently in view of the increasingly harsh business environment. Partnering TM and simplex algorithm promises improved optimisation results and must be pursued to the advantage of metal removal processes worldwide. Generally, in optimisation studies of metal removal processes, the overall objective is to develop and implement a methodology to predict the optimal values of parameters bearing in mind the factors like production rates, lead time and cost-related objectives of the metal removal operations [7] and the energy efficiency problem [8]. Consequently, improved methodologies for the prediction of such parameters are important and necessary pursuits in the area of metal removal process. However, the most pronounced optimisation approach which may appeal to both machinists and researchers is the TM in that it reduces the cost of production.

Four case studies were conducted, involving a drilling case, a case study on milling and two cases on deep drawing. A new approach, TM-SA, is then proposed and tested using the same four case studies, as carried out for the simplex algorithm (SA). Here, it is shown that for the four case studies, the three methods, TM, SA and TM-SA yield comparable results. The major reason for combining TM and SA is to take advantage of experimentation cost, while allowing a large number of variables, which practically exist in industries.

To achieve the goal of improved optimisation, a new methodology, TM-SA is proposed, and the testing and comparison are in three stages. For the first stage, Taguchi method only is used and applied to a set of case studies involving experimental data from the literature. In the second instance, the SA alone is applied in the testing of the four case studies. The third stage involves the integration of TM and SA, as TM-SA in the prediction of the optimal values in all the four case studies considered [9-12]. The data used in the study are purely from the literature as no laboratory experiments were performed by the current authors. In doing this, the literature was searched for relevant studies on the metal removal process. The attention of the authors was directed at papers that have applied the Taguchi's orthogonal array since this is the major input in the SA. Although the problems reported in any array are unique in nature, the use of an orthogonal array in any TM application is pivotal which must be done to obtain credible results.

2. Literature Review

In the metal removal process literature [7,8] there is hardly any other topic that stirs researchers discussions as rigorously as the issue of optimisation of process parameters. In recent times, more attention is devoted to optimisation as more important considerations of energy, economics, environmental and agility issues are incorporated into optimisations for manufacturing sustainability [13,14,15,16,17,8]. The optimal choice of parameters has also been found as an important contribution to productivity growth and cost reduction. For example, [18] reported the significance of optimisation in cutting conditions. They asserted that the optimal selection of cutting conditions led to productivity growth and decrease in process costs.

A review of literature portrays the state-of-the-art and its shortcomings, indicating the need for optimisation models as follows. In cutting processes, [19] optimised the cutting process of the ball-end milling with the use of a genetic algorithm initiated from a previous study [20], portraying a genetic algorithm-based procedure for solving the optimisation method as being effective and efficient. In milling operations, [21] developed optimal conditions for the face-milling operation using genetic algorithm based on parameters that include the number of passes, depth of cut in each pass, speed and feed. In turning processes, [22] presented a hybrid technique based on the differential evolution algorithm for turning operations. For machining, [23] obtained the optimal parameters in the cutting process of multi-pass machining operations by minimizing the unit production cost of converting a cylindrical bar stock into a continuous finished profile. Regarding multi-pass optimisation, [24] developed a methodology that effectively optimised the machining conditions of multi-pass lathe operations.

Another optimisation study on machining was performed in [25] in the dry high-speed turning tests in the selection of optimum tool material, tool geometry and cutting parameters for the turning of 20% Al/SiC metal matrix composites. [26] developed an approach for the optimal sub-division of the depth of cut during multi-pass turning using genetic algorithms. [14] developed a two-phase approach to the minimization of the total machining cost in CNC machining operations with the tool sharing concept and loading duplicate tools for a possible reduction in tooling and tool operating costs, at the same time maintaining feasibility with respect to precedence, tool magazine capacity, tool life covering and tool availability constraints.

In NC machining, [27] contributed to the debate on optimisation methods, namely an integer programming method, which is a method used to automate the cutter selection tasks and reduce total machining time in NC machining operations. In yet another paper on turning processes, [28] developed an optimisation framework for the determination of cutting parameters in machining operations using a genetic algorithm. [29] discussed a machining economics problem to determine the optimum machining conditions and tool allocation simultaneously to minimize the production cost of a multiple operation case, where it is possible to have alternative tools for each operation. The problem of multi-pass face milling operations optimisation was addressed in [30] using a cutting model, which is nonlinear, formulated as a constrained programming problem.

[31] developed optimum cutting conditions in turning by minimizing cost and maximizing production rate. The traditional tool life equation by Taylor was modified and used to predict the tool life. [32] optimised machining parameters in milling operations. On the turning operation, [33] uses a complex cost function. [34] hybridized TM and a differential evolution algorithm for the optimisation of multi-pass turning operations.

Keeping in mind the literature review carried out on the current topic, the following assertions can be made. First, there have been many engineering issues drawn from diverse applications. Optimisation problems have been formulated and solved using these techniques, including genetic algorithm, ant colony optimisation, hybrid of analytical-neural network, hybrids of Taguchi and differential evolution algorithms. Furthermore, a great research was directed to TM; howevert SA as well as TM-SA are not considered in the existing literature.

3. Proposed Methodology

The TM is well known to have the advantage of reducing experimental costs. [35] noted that the TM is used for designing and improving product quality and that it is founded on an orthogonal array for setting up the experiment and it optimises the process parameters by analysing the signal-to-noise (S/N) ratios table and graph. TM is widely known as a powerful method, which is systematic in nature, involving the use of design and analysis of experiments [36,37]. Practitioners and researchers have the intention of using the Taguchi method for improving productivity in the research and development programme of the product while not compromising quality and cost [37]. Unfortunately, a common weakness observed in the use of the Taguchi method is that it optimises only a single performance characteristic [37].

The SA was developed over the years by three great scientists, and George Dantzig in 1939 appears to be the major contributor to the development of simplex. It has the advantage of being easy to use. It allows the usage of many variables and does not require a derivative function. It seems faster than many other algorithms for solving linear problems when complex problems are considered. The simplex algorithm is a solution technique for obtaining optimal values, used in this case for the optimisation of metal removal process parameters.

TM-SA integrates the TM and the SA. It is an analytical method for solving optimisation problems and simultaneously reduces the cost of experimentation, allowing the complexity of treating multiple variables with ease. Moreover, applying both methods (i.e. TM and SA) enables the industrial manager or researcher to take advantage of the merits of both models, including easier and faster attributes. This integration seems to have been proved successful in solving the optimisation of free swell problems [38] and appears useful in this situation. Consequently, it becomes meaningful to utilize an approach to optimisation in the material removal process by comparing TM with the simplex algorithm.

TM-SA is a new method for solving optimisation problems, which has only been seen in one paper. Being a new method, its applicability is dependent on convincing proofs of its suitability to solve a variety of problems. In the metal removal process industries, several areas exist, including drilling, milling, grinding, etc. It is envisaged that treating different problems, with four being a sizeable number, proper validation of the approach could be made. Although the four problems studied are unique, they share the same approach in formulation, and basic assumptions underlying their applications are the same. Therefore, the TM-SA is considered a generalised approach to solving specific metal removal process problems.

The procedure for applying the Taguchi's optimisation method can be found in the literature, and is hence not repeated here [34,39]. However, the three basic desired quality characteristics, viz, the lower-the-better, the larger-the-better and nominal-the-best are stated here in terms of their signal-to-noise (S/N) ratios:

For the "lower-the-better" quality characteristic the S/N ratio is given as

$$\text{S/N } (\eta) = 10 \log 10 \left(\frac{\mu^2}{\sigma^2}\right) \tag{1}$$

where $\mu = \frac{1}{n\sum y_i}$ and $\sigma^2 = \frac{1}{(n-1)}\sum(y_i - \mu)^2$, $y_{1,} y_2, ..., y_n$ are the responses of the coating thickness and 'n' is the number of observation.

For the "larger-the-better" quality characteristic, the S/N ratio is given by

$$\text{S/N } (\eta) = -10\log\left[\frac{1}{n} * \frac{1}{y_i^{\,2}}\right] \tag{2}$$

where n is number of values at each trial condition and y_i denotes each observed value.

For the “nominal-is-best” quality characteristic, the S/N ratio is given by

$$\text{S/N } (\eta) = 10 \log\left[\left(\frac{Y^2}{s^2}\right)\right] \tag{3}$$

where Y is the mean of responses for the given factor level combination and s is the standard deviation of the responses for the given factor level combination.

For the procedure for applying the simplex method, operations research texts, including [40] could be consulted for detail. However, the procedure for applying the Taguchi-simplex, which is the innovation of the current authors, is described as follows

Procedure for applying the TM-SA

The TM-SA procedure is summed up as the integration of the S/N ratios and the optimal TM values, respectively, into the objective function and parametric constraints of the simplex algorithm and solving as an optimisation problem. The desired quality characteristics used for the TM are used to define the direction of optimisation in the TM-SA. A lower-the-better quality characteristic is considered as a minimisation problem, while a higher-the-better quality characteristic is translated as a maximisation problem.

The S/N ratios are integrated into the objective function of the simplex algorithm as coefficients of the variables subject to the constraints of the problem. The lowest level of the factors used before the Taguchi’s optimisation is used as the lower parametric constraints, while the optimal values obtained by the TM are used to define the upper parametric constraints. This is done in order to obtain improved optimal results. The optimisation problem is expressed in a standard form by the addition of slack and surplus variables as required to the parametric constraints. The non-negativity function of the variables is defined while the objective function is re-written to obtain the starting TM-SA tableau.

The iteration of the tableau using the Gauss-Jordan row operation begins by using the optimality and feasibility conditions to obtain the entering and leaving variables. Iteration of the tableaus continues to optimality. The optimal tableau is reached when none of the non-basic variables associated with the objective function row have negative or positive coefficients respectively, for the minimisation or maximisation problem. The optimal values for the variables are given in the solution column of the optimal tableau, while the values are interpreted in an interpretation table.

4. Application of the Proposed Methodology

In this section, the proposed method is explained in a step-by-step manner, supplemented with its flow chart having a closed loop (Figure 1). The justification of using the TM-SA jointly is given, clearly stated with the assumptions, and the drilling process is considered. TM-SA combines the advantages of TM and the SA. This new method combines the experimental cost advantage with the opportunity of using an extensive array of variables with little or no difficulty in computations. The basic assumption guiding the use of the TM-SA is that the variables are linear in their relationship with one-another.

Four case studies are considered both to verify and validate the accuracy of the proposed methods in the current paper. For the first case, [41] provided experimental data related to surface roughness evaluation in an environment of high-speed flat end milling process using wet cutting conditions. The milling variables whose experimental data were collected are the spindle speed, feed rate, depth-of-cut, and step over. In the second case study, [39] dealt with the determination of the effects of forming parameters, including fluid pressure, friction coefficient of blank/punch interface and die entrance radius and the amount of gap between die rim block and blank holder, on the quality of part formability in the process of hydrodynamic deep drawing. In case three, [42] studied the production of cylindrical cups with experimental tests carried out on the flange, die radius shoulder, wall thickness, punch radius shoulder, punch radius and the bottom of the cups by focusing on the following parameters: die/shoulder radius/shoulder radius, blank holder force, friction between sheet and die/punch/holder. In a drilling case study, the fourth testing data, [43] collected experimental data from drilling operations of stainless steel SS304 with the drilling parameters such as spindle speed, feed rate and slurry concentration.

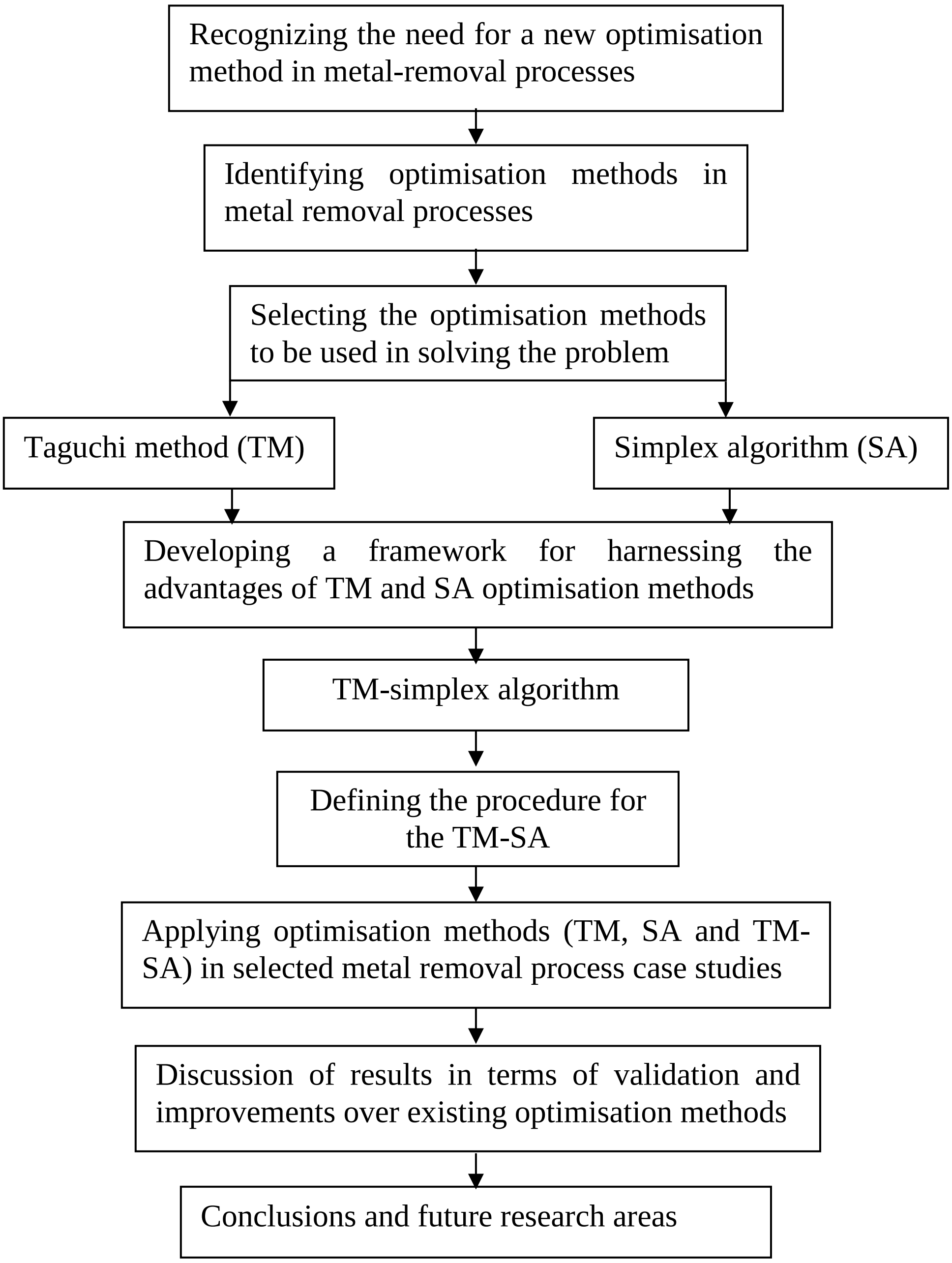

Figure 1: Research scheme for the metal removal process using TM-SA

Case study 1: Optimisation of surface roughness in high-speed flat-end milling [41]

(a) TM

Tables 3 and 4 of [41] contain the factors and variable levels ,and other information used in the experimental plan, which yields the average S/N ratios indicated in Table 1.

The optimum level of each parameter based on the quality characteristics of "smaller-the-better" of the S/N ratios was noted as (A: 5th level; B: 1st level; C: 2nd level; D: 4th level). The optimal parametric setting of A5, B1, C2, D4 is translated in Table 2. By varying each of the process control parameter on the output response it can be seen that parameters A and B showed less variations with the output responses.

Table 1: Average S/N ratio responses

	Spindle speed, S_s (rpm) (A)	Feed rate, F_r (mm/min) (B)	Depth of cut, D_c (mm) (C)	Step over, S_o (mm) (D)
Level 1	-11.703	**-13.859**	-12.477	-12.479
Level 2	-12.11	-13.012	**-12.506**	-10.7
Level 3	-12.51	-12.451	-12.487	-12.487
Level 4	-12.78	-11.875	-12.38	**-12.51**
Level 5	**-12.969**	-11.497	-12.477	-12.475
Optimum level	A_5	B_1	C_2	D_4
Max – Min	1.266	2.362	0.126	1.787
Rank	3	1	4	2

Table 2: Optimal values for the surface roughness parameters in high speed flat end milling process

Parameters	S_s (rpm)	F_r (mm/min)	D_c (mm)	S_o (mm)
Optimal value	10,000	640	0.3	4

(b) SA

$$\text{Minimise } SR = \sum_{p=1}^{q} \phi_p k_p \tag{4}$$

Subject to:

$$\text{Spindle speed, } S_s \text{ (cm}^3\text{)}: \quad 4000 \leq S_s \geq 10000 \tag{5}$$

$$\text{Feed rate, } F_r \text{ (mm/min)}: \quad 640 \leq F_r \geq 4800 \tag{6}$$

$$\text{Depth of cut, } D_c \text{ (mm)}: \quad 0.1 \leq D_c \geq 0.9 \tag{7}$$

$$\text{Step-over, } S_o \text{ (cm}^3\text{)}: \quad 1 \leq S_o \geq 5 \tag{8}$$

Using the above given constraints, where $\phi_1, \phi_2, \phi_3, \phi_4 = 1$ and $k_1 = Ss$, $k_2 = Fr$, $k_3 = D_c$, $k_4 = S_o$, (4) can be written as

Minimize $SR = S_s + F_r + D_c + S_o$ (4a)

Equations (4) to (8) can be further broken down since they both have "$\leq$" attached to them. Thus we have

Minimize $SR = S_s + F_r + D_c + S_o$

subject to

Spindle speed, S_s (cm^3):

$S_s \geq 4000$ (5a)

$S_s \leq 10000$ (5b)

Feed rate, F_r (mm/min)

$F_r \geq 640$ (6a)

$F_r \leq 4800$ (6b)

Depth of cut, D_c (mm):

$D_c \geq 0.1$ (7a)

$D_c \leq 0.9$ (7b)

Step over, S_o (cm^3):

$S_o \geq 1$ (8a)

$S_o \leq 5$ (8b)

expressing the surface roughness optimisation problem in standard form, where slack and surplus variables are used. Then, J_1, J_2, J_3 and J_4 are used for (5) to (8) respectively.

Thus, the following equations are valid

$S_s - J_1 = 4000$ (9a)

$S_s + J_1 = 10,000$ (9b)

$F_r - J_2 = 640$ (10a)

$F_r + J_2 = 4800$ (10b)

$D_c - J_3 = 0.1$ (11a)

$D_c + J_3 = 0.9$ (11b)

$S_o - J_4 = 1$ (12a)

$S_o + J_4 = 5$ (12b)

The non-negativity constraint is given as

$S_s, F_r, D_c, S_o \geq 0$

Assume that $J_1 = -4000$ or 10000, $J_2 = -640$ or 4800, $J_3 = -0.1$ or 0.9, J_4 = -1 or 5, where the variables J_1, J_2, J_3 and J_4 are the slacks associated with the respective constraints. This is followed by writing the objective equation as

$$\text{Minimize } SR - S_s - F_r - D_c - S_o = 0$$

The optimality condition requires picking the variable with the highest negative coefficient as the entering variable. In this case, all the variables have the same negative coefficient of -1. Therefore, any of the non-basic variables could be picked as the entering variable. The feasibility condition requires that the leaving variable should have the minimum non-negative ratio. Hence, D_c becomes the entering variable, while J_3 becomes the leaving variable. J_3 is replaced in the basic column with D_c, and a new set of variables is produced. The swapping process is done using the Gauss-Jordan row operations to produce the next simplex tableau. The iteration process continues to produce new simplex tableaus and new sets of variables till the optimal tableau is reached, as seen in Table 3.

Table 3: Optimal SA tableau

Basic	*SR*	S_s	F_r	D_c	S_o	J_1	J_2	J_3	J_4	*Solution*
SR	1	0	0	0	0	1	1	1	1	14805.9
J_1	0	1	0	0	0	1	0	0	0	10000
J_2	0	0	1	0	0	0	1	0	0	4800
J_3	0	0	0	1	0	0	0	1	0	0.9
J_4	0	0	0	0	1	0	0	0	1	5

Here, none of the *SR* coefficients associated with the non-basic variables are negative. The interpretation of the table is given in Table 4.

Table 4: Interpretation table

	Optimum values for:	
Decision variable	SA	TM-SA
S_s	10,000	10,000
F_r	4,800	625
D_c	0.9	0.3
S_o	5	4

The following recommendations can be deduced: Use a spindle speed of 10,000 and 10,000 rpm; a feed rate of 4800 and 625 mm/min, a depth-of-cut of 0.9 and 0.3 mm, and a step-over of 5 and 4 mm, respectively, for simplex and TM-SA.

(c) TM-SA

The present authors have used the TM to optimise the surface roughness of a high-speed flat end milling process under wet cutting conditions subject to the parameters and levels in Table 3 of [41]. The result produced an optimal parametric setting which has been translated. The corresponding average S/N ratios for the optimum parametric levels are -12.97,-13.86, -12.51 and -12.51 for A_5, B_1, C_2 and D_4, respectively. The S/N ratios are integrated into the objective function of the simplex algorithm, while the optimal parametric setting obtained from the TM is used to define the lower and upper limits of the constraints making it the TM-SA.

Thus, we have

$$\text{Minimize } SR = \sum_{p=1}^{q} \phi_p k_p \tag{4}$$

subject to:

$$\text{Spindle speed, } S_s \text{ (rpm):} \quad 4000 \leq S_s \geq 10000 \tag{5}$$
$$\text{Feed rate, } F_r \text{ (mm/min):} \quad 640 \leq F_r \geq 640 \tag{6}$$
$$\text{Depth of cut, } D_c \text{ (mm):} \quad 0.1 \leq D_c \geq 0.3 \tag{7}$$
$$\text{Step over, } S_o \text{ (mm):} \quad 1 \leq S_o \geq 4 \tag{8}$$

Simplifying the constraints further, we have,

$$\text{Spindle speed, } S_s \text{ (rpm):} \quad 0.00025 S_s \geq 2.5 \tag{14}$$
$$\text{Feed rate, } F_r \text{ (mm/min):} \quad 0.00156 F_r \geq 1 \tag{15}$$
$$\text{Depth of cut, } D_c \text{ (mm):} \quad 10 D_c \geq 3 \tag{16}$$
$$\text{Step-over, } S_o \text{ (mm):} \quad 1 S_o \geq 4 \tag{17}$$

Using the above given constraints, where $\phi_1, \phi_2, \phi_3, \phi_4 = 1$ and $k_1 = Ss$, $k_2 = Fr$, $k_3 = D_c$, $k_4 = S_o$, (4) can be written as

$$\text{Minimise } SR = 12.97\, S_s + 13.859\, F_r + 12.51\, D_c, +12.51\, S_o \tag{18}$$

subject to

$$\text{Spindle speed, } S_s \text{ (rpm):} \quad S_s \leq 2.5 \tag{19}$$
$$\text{Feed rate, } F_r \text{ (mm/min):} \quad F_r \leq 640 \tag{20}$$
$$\text{Depth of cut, } D_c \text{ (mm):} \quad D_c \leq 3 \tag{21}$$
$$\text{Step over, } S_o \text{ (mm):} \quad S_o \leq 4 \tag{22}$$

Expressing the surface roughness optimisation problem in standard form, where slack and surplus variables are used. Then J_1, J_2, J_3 and J_4 are used for equations (19) to (22), respectively.

Thus the following equations are valid

$$12.97\, S_s + J_1 = 2.5 \tag{23a}$$
$$12.97\, S_s - J_1 = 2.5 \tag{23b}$$
$$13.86\, F_r + J_2 = 1 \tag{24a}$$
$$13.86\, F_r - J_2 = 1 \tag{24b}$$
$$12.51\, D_c + J_3 = 3 \tag{25a}$$
$$12.51\, D_c - J_3 = 3 \tag{25b}$$
$$12.51\, S_o + J_4 = 4 \tag{26a}$$
$$12.51\, S_o - J_4 = 4 \tag{26b}$$

The non-negativity constraint is given as

$$S_s, F_r, D_c, S_o \geq 0$$

Assume that $J_1 = 2.5$ or -2.5, $J_2 = 1$or-1, $J_3 = 3$ or -3, $J_4 = 4$ or -4, where the variables J_1, J_2, J_3 and J_4 are the slacks associated with the respective constraints. This is followed by writing the objective equation as

$$\text{Minimize } SR - 12.97S_s - 13.859F_r - 12.51D_c - 12.51S_o = 0.$$

Following the optimality condition, F_r becomes the entering variable while J_2 becomes the leaving variable using the feasibility condition. J_2 is replaced in the basic column by F_r, and a new set of variables is produced. The swapping process is completed using the Gauss-Jordan row operations to produce the next simplex tableau. The iteration of the tableau continues to produce new set of variables till the optimal tableau is reached in Table 5.

Table 5: Optimal TM-SA tableau

Basic	*SR*	S_s	F_r	D_c	S_o	J_1	J_2	J_3	J_4	*Solution*
SR	1	0	0	0	0	51880	8662.5	1.251	12.51	146,868.79
S_s	0	1	0	0	0	1	0	0	0	10000
F_r	0	0	1	0	0	0	1	0	0	625
D_p	0	0	0	1	0	0	0	1	0	0.3
S_o	0	0	0	0	1	0	0	0	1	4

Since none of the non-basic variables in the SR row have positive coefficients, the last tableau can be said to be optimal. The optimal values of the non-basic variables are given in the solution column of Table 5. The interpretation of the table is given in the interpretation table in Table 4.

Case study 2: Optimisation of forming parameters in sheet hydrodynamic deep drawing process [39]

(a) TM

[39] used the FEM-based Taguchi method to optimise the forming parameters of a hydrodynamic deep drawing process. The desired quality characteristic of "lower-the-better" was used to select the optimal parametric levels from the obtained S/N ratios for the different cups that were produced in the deep drawing process. The optimal parametric settings are $A_2B_3C_1D_3$, $A_2B_3C_1D_3$, $A_1B_3C_1D_3$ for the parabolic, hemispherical and cylindrical cups respectively, as seen in Table 6.

Table 6: Optimal values for forming parameters in sheet hydrodynamic deep drawing

Cup/ Parameters	Fluid pressure (MPa)	Friction coefficient (μ)	Gap (mm)	Die entrance radius (mm)
Parabolic	20	0.20	0	5
Hemispherical	20	0.20	0	5
Cylindrical	10	0.20	0	5

(b) SA

The SA was used to optimise the parameters using the appropriate factors and levels obtained from Table 1 of [39]. Since the procedure is repetitive, we shall only provide the final answer from the optimal tableau (Table 7).

Table 7: Interpretation table for the simplex algorithm optimal values

Decision variable	Optimum value
F_p	20
F_c	0.2
G	0.1
D_r	5

The following recommendations are given:

Fp: The SA suggests using a fluid pressure of 20 MPa for the deep drawing process

Fc: The SA suggests using a friction coefficient of 0.2 μ for the deep drawing process.

G: The SA recommends the use of a gap of 0.1 mm for the deep drawing process.

Dr The SA recommends the use of a die entrance radius of 5 mm for the deep drawing process.

(c) TM-SA

[39] used the Taguchi method to optimise the forming parameters in the sheet hydrodynamic deep drawing process for producing parabolic, hemispherical and cylindrical cups. The optimum parametric setting for the parabolic and hemispherical cups was found to be $A_2B_3C_1D_3$ while the cylindrical cups have an optimum parametric setting of $A_1B_3C_1D_3$. Because the three cups have different average S/N ratios and optimal Taguchi values, the TM-SA would be applied to them separately.

(i) Parabolic cup

For the parabolic cup, the Taguchi's optimum parametric setting is translated to the average S/N ratios as follows [$A_2B_3C_1D_3$] = [12.3, 12.47, 12.2, 11.94]. The final answer for this is as shown below (Table 8).

(ii) Hemispherical cup

For the hemispherical cup, the Taguchi's optimum parametric setting is translated to the average S/N ratios as follows [A2B3C1D3] = [19.78, 19.84, 19.82, 19.18]. The final answer is in Table 8.

(iii) Cylindrical cup

For the cylindrical cup, the Taguchi's optimum parametric setting is translated to the average S/N ratios as follows [A1B3C1D3] = [18.59, 18.57, 18.53, 0.95]. The final answer is in Table 8.

Table 8: Interpretation table for the TM-SA optimal values

	Optimum values for:		
Decision variable	Parabolic cup	Hemispherical cup	Cylindrical cup
F_p	20	20	10
F_c	0.2	0.2	0.2
G	0.1	0.1	0.1
D_r	5	5	5

The following recommendations are given:

Fp: The TM-SA recommends the use of 20, 20 and 10 MPa fluid pressure, respectively, for parabolic, hemispherical and cylindrical cups.

Fc: The TM-SA recommends the use of 0.2 μ friction coefficient, respectively, for the respective parabolic, hemispherical and cylindrical cups.

G: The TM-SA recommends the use of 0.1 mm gap respectively, for the parabolic, hemispherical and cylindrical cups.

Dr: The TM-SA recommends the use of a die entrance radius of 5 mm respectively, for the respective parabolic, hemispherical and cylindrical cups.

Case study 3: Optimisation of Cup Deep drawing parameters of ST14 Sheet [42]

(a) TM

The optimisation of the thickness distribution parameters in cup deep drawing of ST14 sheet was carried out by [42] using the six parameters and levels (Table III of [42]) This was done for six different locations of the cup. They also presented the optimal values of the parameters for each of the location in Table VI. Using location 1 for our case study, we carry out the simplex algorithm and TM-SA optimisation method on the location 1.

(b) SA

The results of the simplex algorithm is presented alongside the optimal results of the TM-simplex algorithm (Table 10).

(c) TM-SA

The Taguchi method has been used to optimise the distribution of thickness parameters in a cup deep drawing process of ST14 sheet subject to the parameters and levels listed in Table 9. The optimum parametric level for the deep-cup drawing process parameters for the six different locations is presented. The average S/N ratios for each of the parameters were obtained as follows (Table 9). Using location 1 for our case study, while the average S/N ratios are integrated into the objective function, we have the TM-SA.

Table 9: Average S/N ratios for the parameters

D_r	P_r	BHF	M_1	M_2	M_3
0.00108	0.00108	0.001082	0.001081	0.001081	0.001081

The parameters would be further optimised using the lowest levels of the parameters from Table A as the initial constraints while the optimum parametric values from the TM will be the higher constraints in the TM-SA. The final results are as follows (Table 10).

Table 10: Interpretation table

	Optimal values for:	
Decision variable	Simplex	TM-simplex
D_r	12	11.98
P_r	12.5	12.5
BHF	18	18
M_1	0.22	0.22
M_2	0.28	0.1
M_3	0.22	0.22

The following recommendations are given:

Dr: The SA and TM-SA suggests the use of a die radius of 12 and 11.98 mm, respectively, for the cup deep drawing process.

Pr: The SA and TM-SA suggests the use of a punch radius of 12.5 mm, respectively, for the cup deep drawing process.

BHF: The SA and TM-SA recommends a blank holder force of 18 kN, respectively for the cup deep drawing process.

Dr: The SA and TM-SA recommends a friction force of 0.22 kN between the sheet and the die, respectively for the cup deep drawing process

Dr: The SA and TM-SA recommends a friction force of 0.28 and 0.1 kN between the sheet and the punch, respectively for the cup deep drawing process

Dr: The SA and TM-SA recommends a friction force of 0.22 kN between the sheet and the holder, respectively for the cup deep drawing process

Case study 4: Prediction of optimal process parameters for abrasive assisted drilling of SS304 [43]

(a) TM

The factors and levels as well as the result matrix for the 3-level experimental design considering three process parameters namely slurry concentration, feed and speed have been presented in Tables 3 and 4 respectively, of [43]. This was adopted as the orthogonal array and the S/N ratios were calculated using "lower-the-better" quality characteristics in order to reduce the surface roughness and obtain better surface finish. The average S/N ratios for each of the parametric levels are given in Table 11.

Table 11: Average S/N ratio

	A	B	C
Level 1	-13.33	-13.65	-12.84
Level 2	- 13.3	-13.24	-13.46
Level 3	-13.18	-12.86	-13.72

The optimum parametric setting is given as $A_1B_1C_3$ which is interpreted by Table 12.

Table 12: Taguchi's optimum parametric setting for the parameters

Parameters	Slurry concentration (%)	Feed (mm/min)	Speed (rpm)
Optimal values	20	32.5	740

(b) SA

The process parameters and levels for the abrasive assisted drilling of SS304 are shown in [43]. Using the simplex algorithm, the final solution is as follows (Table 13).

(c) TM-SA

The Taguchi's optimum parametric levels for the abrasive assisted drilling of SS304 has been given. The surface roughness parameters would be optimised using the laid down procedure in order to obtain improved results. The TM-SA optimal results are presented in Table 13.

Table 13: Interpretation table

	Optimum values for:	
Decision variable	SA	TM-SA
Sc	30	20
F	78	33.33
S	740	737.93

The following recommendations are given:

Sc: The SA and TM-SA suggests the use of a slurry concentration of 30 and 20 %, respectively, for the abrasive assisted drilling process.

F: The SA and TM-SA suggests the use of a feed of 78 and 33.33 mm/min, respectively, for the abrasive assisted drilling process.

S: The SA and TM-SA suggests the use of a speed of 740 and 737.93 rpm, respectively, for the abrasive assisted drilling process.

The following is a summary of results obtained in this study (Tables 14 to d).

Table 14a: Optimal results for surface roughness parameters in high-speed flat-end milling [41]

Parameters	TM	SA	TM-SA
S_s (rpm)	10,000	10,000	10,000
F_r (mm/min)	640	4800	625
D_c (mm)	0.3	0.9	0.3
S_o (mm)	4	5	4

Table 14b: Optimal results for forming parameters in sheet hydrodynamic deep drawing using FEM-based TM [39]

Cups	Parameters	TM	SA	TM-SA
Parabolic	F_p (MPa)	20	30	20
	F_c (μ)	0.2	0.2	0.2
	G (mm)	0	0.1	0.1
	D_r (mm)	5	5	5
Hemispherical	F_p (MPa)	20	30	20
	F_c (μ)	0.2	0.2	0.2
	G (mm)	0	0.1	0.1
	D_r (mm)	5	5	5
Cylindrical	F_p (MPa)	10	30	10
	F_c (μ)	0.2	0.2	0.2
	G (mm)	0	0.1	0.1
	D_r (mm)	5	5	5

Table14c: Optimal results for parameters affecting the distribution of thickness in cup deep-drawing of ST14 sheets [43] – Location 1

Parameters	TM	SA	TM-SA
D_r (mm)	12	11.98	11.98
P_r (mm)	12.5	12.5	12.5
BHF (KN)	18	18	18
M_1 (N)	0.22	0.22	0.22
M_2 (N)	0.1	0.28	0.1
M_3 (N)	0.22	0.22	0.22

Table 14d: Optimal results for parameters for abrasive-assisted drilling of SS304 [43]

Parameters	TM	SA	TM-SA
S_c (%)	20	30	20
F (mm/min)	32.5	78	33.33
S (RPM)	740	740	737.93

5. Results and Discussion

In case study 1 [41], the optimal results of the high-speed flat-end milling process from the three methods indicate that the maximum spindle speed will be used. The minimum feed rate of 640 mm/min obtained from the TM shows that surface roughness will be reduced, while a feed rate of 4800 mm/min obtained from the simplex algorithm indicates that the surface roughness may not be overcome as a result of high rate of feed. The TM-SA presents an improvement on the TM results with a lower feed rate of 625 mm/min. This will ensure improved smoothness and the reduction of the surface roughness to the barest minimum. Although, the simplex algorithm optimal results may ensure a faster production process as a result of high consumption of material due to the high-speed rate, depth of cut and step-over. The Taguchi-simplex offers a better surface finish than the TM because a lower amount of material is consumed at the same speed.

The forming parameters from case study 2 [39] shows a consistency of results of the TM and TM-SA, except for allowing a gap of 0.1 mm by the TM-SA. This allowance of 0.1 mm gap may ensure a smoother production process, reduce the incidence of wrinkling and ease the removal of the cups. The simplex algorithm optimal results show the use of maximum fluid pressure which is crucial to the deep drawing process. This may ensure smoothness of the cups produced.

The optimal results for the thickness distribution parameters in case study 3 shows a consistency of results by the three optimisation methods except for the die radius. [42] noted that an increase in the die radius can cause higher possibility of wrinkling in the cups. The SA and TM-SA obtained a new optimal value of 11.98 mm die radius. The new optimal value of the die radius will decrease the possibility of wrinkling in the produced cups and improve the deep drawing process of ST14 sheet.

The optimal results for the case study in [43] showed that the TM and TM-SA used a slurry concentration of 20 %. The simplex algorithm uses a slurry concentration of 30 % that may help to reduce friction and smoothness of the drilling process. The large amount of feed required by the simplex algorithm may affect the drilling process and still ensure the presence of surface roughness. The TM-SA gives an optimal speed of 737.93 rpm, which is less than 740 rpm obtained by the other two methods. The TM offers the best optimal combination of parameters providing maximum speed and minimum feed for the drilling process.

6. Conclusions

In this paper, a different direction for process optimisation is taken by employing the combined TM-SA for the optimal parametric setting of a manufacturing process. The details of the method are provided together with four case studies. The significant reason for combining TM and SA is to take advantage of experimentation cost, while allowing a large number of variables, which practically exist in the industry.

The first case study from [41] showed that the Taguchi-simplex method validates the existing optimal values obtained by the Taguchi method. For the second case study in [39], the Taguchi-simplex method validates existing TM results. The third case study in [42] revealed that the TM-simplex algorithm found a friction between sheet and punch at 0.28 kN, while the optimal value for the die radius was found to be 11.98 mm. The optimal values for the other parameters were maintained. For the fourth case study in [43], the TM-SA yielded 33.33 mm/min and 737.93 rpm of feed and speed, respectively. The results obtained from using these four literature cases were compared with those of the TM and the simplex method. The proposed TM-SA showed optimisation results with certain superior features in one of the tested cases and equivalent result in others.

The optimal results show that existing optimal parametric values can be validated or improved upon. The application of the proposed TM-SA to complex real world problems in machining and manufacturing in general are left for future studies. A revised simplex technique and introducing some levels of prioritization of parameters may be considered for future research. An additional future research area is to consider tracking uncertainties in the parametric captures using fuzzy logic principles. Furthermore, potential applications of the proposed approach by material type are its usage in machining mild steel, grey cast iron, brass and aluminium with HSS, carbide and carbon steel, respectively, used as tools.

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