2017

Drilling reconfigurable machine tool selection and process parameters optimization as a function of product demand

Ana Vafadar
Edith Cowan University, a.vafadarshamasbi@ecu.edu.au

Kevin Hayward
Edith Cowan University, kevin.hayward@ecu.edu.au

Majid Tolouei-Rad
Edith Cowan University, m.rad@ecu.edu.au

10.1016/j.jmsy.2017.08.004
This is an Author's Accepted Manuscript of: Vafadar, A., Hayward, K., & Tolouei-Rad, M. (2017). Drilling reconfigurable machine tool selection and process parameters optimization as a function of product demand. *Journal of Manufacturing Systems*, *45*, 58-69.

Drilling reconfigurable machine tool selection and process parameters optimization as a function of product demand

Ana Vafadar [a] *, Kevin Hayward [a], Majid Tolouei-Rad [a]

[a] *School of Engineering, Edith Cowan University (ECU), Perth, Australia*

ARTICLE INFO

ABSTRACT

Special purpose machines (SPMs) are customized machine tools that perform specific machining operations in a variety of production contexts, including drilling-related operations. This research investigates the effect of optimal process parameters and SPM configuration on the machine tool selection problem versus product demand changes. A review of previous studies suggests that the application of optimization in the feasibility analysis stage of machine tool selection has received less attention by researchers. In this study, a simulated model using genetic algorithm is proposed to find the optimal process parameters and machine tool configuration. During the decision-making phase of machine tool selection, unit profit is targeted as high as possible and is given by the value of the following variables: SPM configuration selection, machining unit assignment to each operation group, and feed and cutting speed of all operations. The newly developed model generates any random chromosome characterized by feasible values for process parameters. Having shown how the problem is formulated, the research presents a case study which exemplifies the operation of the proposed model. The results show that the optimization results can provide critical information for making logical, accurate, and reliable decisions when selecting SPMs.

Keywords Special purpose machines (SPMs). Drilling configurable machine tool. Optimization. Feasibility analysis. Machine tool selection.

1. Introduction

Today's dynamic market demand has led industries to utilize quick and responsive manufacturing systems [1-3]. Special purpose machines (SPMs) are a new paradigm of reconfigurable machine tools (RMTs) which have the customized flexibility to enable them to perform drilling-related operations [4, 5]. These machines include sliding and machining units, assembly components, indexing or sliding tables, control systems, and accessories (Fig.1). Machining unit has different types which are selected based on the part properties, and required power [6]. Their efficiency is based on their reconfigurability, which enables them to be cost effective and adaptable in rapidly changing markets. Reconfigurability makes it possible for SPMs to apply minor changes to the configuration of the machine by repositioning units and accessories and changing configurations in order to make a new part [7, 8] Moreover, their capabilities change for each configuration, so process planning parameters can also be reconfigured. While there are several studies of RMTs [9-12]; few have addressed SPMs and a review of the literature indicates that the consideration of SPM configuration type, machining unit assignment, and machining parameters have largely been ignored

In recent decades, many researchers have explored computer aided process planning (CAPP). Xu, Wang and Newman [13] comprehensively reviewed recent developments and future perspectives for CAPP. Li, Liu, Li, Landers and Tang [14] asserted that process planning optimization includes optimal machining parameters and machining sequence generation. Accordingly, most process planning studies have focused on generating optimum machining parameters [14, 15]. Other studies have focused on process planning and operation sequencing [16]. But today CAPP faces new challenges which have drawn researchers' attention to the dynamic and ever-changing competitive market. Since product demand may change in this competitive market, the appropriate utilization of SPM configuration and process parameters is becoming more important for manufacturers. Marri, Gunasekaran and Grieve [17] defined process planning as the changing configurations in order to make a new part decision-making activity for the selection of machines and the machining process needed to produce a part. Determination of optimal process parameters may affect productivity, operation time, and production cost. Therefore, appropriate selection of SPM configuration and process parameters may significantly influence the decision to use SPMs instead of other machine tools at the feasibility analysis stages.

Feasibility analysis for utilising a machine tool from among available alternatives became a difficult and important issue in Today's market for manufacturers. Accordingly, selecting appropriate machine tool has been investigated from different perspectives. A majority of researchers utilized multi-attribute decision-making tools to find an appropriate choice [18-21]. These methods are based on the ranking and opinions of experts and decisions may be inconsistent. Some machine tool selection studies focused on cost analysis methods such as advanced machine tools and material handling systems [22, 23], but few considered reconfigurable machine tools. [2], Vafadar, Tolouei-Rad and Hayward [8] proposed an economic analysis model for selecting SPM relative to other machine tools. A key challenge for making accurate decision is comparing optimal SPM versus other machine tools which is an important process as it may significantly influence the final decision.

In a highly competitive market, manufacturers must respond quickly to requests. Heuristic optimization techniques such as genetic algorithm (GA), simulated annealing (SA), and Tabu search (TS) meet the requirement for fast optimization of multi-variable problems [24]. A review on the optimization techniques showed that evolutionary techniques are useful tools which are utilized broadly for different manufacturing problems [24-26]. Youssef and ElMaraghy [27] developed a GA optimization model to find a feasible configuration of reconfigurable manufacturing systems. The model minimized the capital investment of RMS configurations to find the optimum number of parallel machines per stage and operation assignments. Guldogan [28] proposed a model integrating a knowledge-based expert system and GA to consider qualitative and quantitative parameters for machine selection and operation selection. Cus and Balic [15] proposed an optimization method based on genetic algorithms (GA) for generating cutting parameters in flexible manufacturing systems (FMS). Chaube, Benyoucef and Tiwari [29] proposed a new algorithm to generate dynamic process planning, considering the time and cost of production for reconfigurable machine tools. The considered variables in the model presented by Chaube, Benyoucef and Tiwari [29] are part, operation, machine, configuration, tool, and tool approach direction. There has been some research about CAPP for reconfigurable machine tools and manufacturing systems, while the integrated optimization of machining parameters and process plan for SPMs have not been adequately addressed.

From the above it can be found that although there are some publications on reconfigurable machine tools, application of optimization methods in manufacturing discipline, machine tool selection problem, and CAPP; a research which combines these concurrently in order to investigate the effect of optimization process on the machine tool selection problem at the investment stage has not yet been adequately addressed in the literature.

The aim of this research is considering the benefits of GA for CAPP when finding the most appropriate combination of process parameters and SPM configuration, in order to maximize the unit profit of SPMs. In optimizing process planning parameters, GA [15, 30]:

(1) is able to run complex objective functions;

(2) can perform optimization processes successfully for any discrete or continuous variables;

(3) may be integrated with any simulated model;

(4) handles any linear and non-linear relations between inputs and outputs;

(5) is a simple and quick method.

Accordingly, a simulated model using GA is introduced and applied to a case study. Results show that selecting appropriate SPM configuration and process parameters can significantly influence decisions made at the early stages of investment on a machine tool.

This paper is organized as follows: Section 2 explains the formulation of the optimization problem. Section 3 describes the integrated simulation-based GA method. Section 4 illustrates a case study to validate the method and includes the results and discussion relating to the effect of optimization on the feasibility analysis outcomes. Key conclusions are provided in Section 5.

2. Formulation of the problem

A practical method is proposed to determine the most cost effective process parameters and SPM configuration to meet competitive market demand at the feasibility analysis stage. The problem is considered in the context of finding optimal cutting parameters, including cutting speed and feed, the

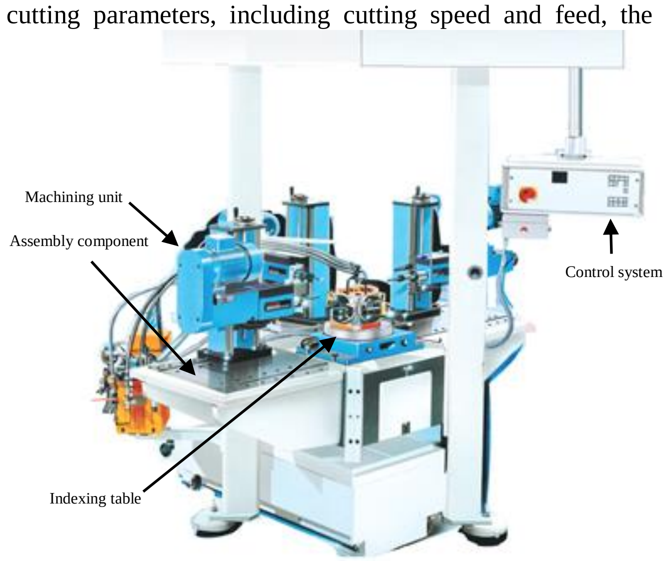

Fig.1. SPM configuration [32].

assignment of machining units to each operation, and the configuration of the SPM (including the number of stations and the assignment of operational groups, and loading and loading operations for the stations). The methodology has three phases, which are outlined below

(1) Formulating the optimization model.
- Defining the objective function
- Defining decision variables
- Defining constraints
- Structuring the genetic algorithm model

(2) Simulating the part production by an SPM based on the cost mathematical model, as proposed by Vafadar, Tolouei-Rad and Hayward [8] and integrating it in to the GA method.

(3) Evaluating optimization results.
- Decoding, formatting, and analyzing the optimization results
- Comparing the results of the feasibility analysis before and after performing optimization at the decision-making stage
- Observing and discussing the effect of optimum results on the decision-making process.
- Finding the best combination of optimum process parameters, machining units, and SPM configurations.

2.1. Optimization model

In the initial decision-making stage for utilizing an SPM, the aim is to find a combination of configuration and process parameters which maximize the unit profit in order to find a reliable way to compare any solution with other alternatives. For the optimization model developed below, the following assumptions are specified:

- The maximum number of machining units which can be utilized in each station is two.
- The maximum number of stations which can be considered in the SPM layout is twelve.
- The SPM layout type can be single- or multiple- station.
- The SPM multiple-station type can be rotary or sliding.
- Loading and unloading can be assigned to a single or two separate stations.

2.1.1 Decision variables

The decision variables for this model are as below:

(a) Cutting speed of each operation group

(b) Feed of each operation group

(c) Machining unit allocation to each operation group

(d) Configuration type

(e) Number of stations

(f) Allocation of loading and unloading activities to the stations

Each operation group may include one or more similar holes which can be drilled by a single spindle or a multiple spindle head.

2.1.2 Objective function

The objective function, maximum unit profit, is developed based on the following cost mathematical model. The unit profit can be calculated by

$$Profit = D\sum_{j=1}^{t} S_{p_j}(1+i)^{-j} - C_{total} \tag{1}$$

$$C_{total} = C_{mt} + \sum_{j=1}^{t} C_{material_j}(1+i)^{-j} - S\,(1+i)^{-t} + \sum_{j=1}^{t} C_{machining_j}(1+i)^{-j} + \sum_{j=1}^{t} C_{maintenance_j}(1+i)^{-j} + \sum_{j=1}^{t} C_{overhead_j}(1+i)^{-j} \tag{2}$$

$$Unit\ profit = \frac{Profit}{D\times t} \tag{3}$$

Accordingly, the objective function is expressed as below:

$$\begin{aligned} Max\ Unit\ profit = {} & K_1 - [(Roundup(K_2\,T_{m1})(C_{mu}+C_{it} \\ & +K_3)] + K_4 - [K_5 \times Roundup(K_2\,T_{m1})(C_{mu}+C_{it} \\ & +K_3) + \sum_{j=1}^{t}(1+i)^{-j}\,(K_{6j}\,T_{mj} + K_{7j}\sum_{k=1}^{N_d} v_{kj}^{n-1}\,f_{kj}^{-1}) \\ & +(\sum_{j=1}^{t}(1+i)^{-j}\,K_{8j}\sum_{k=1}^{N_d} v_{kj}^{n-1}\,f_{kj}^{-1}) \\ & +\textstyle\sum_{j=1}^{t}(1+i)^{-j}\,(K_{9j}\,T_{m\,j})\,] \end{aligned} \tag{4}$$

Where total machining/cycle time for each production year in the above equation can be expressed by

$$\begin{aligned} T_m = {} & \max\,\{\max\{K_{10_k}\ v_k^{-1}\,f_k^{-1} \big| k = 1,\ldots,N_d\},K_{11},K_{12}\} \\ & + K_{13}\sum_{k=1}^{N_d} v_k^{n-1}\,f_k^{-1} + T_i \end{aligned} \tag{5}$$

2.1.3 Constraints

Several constraints are applied to the optimization model, as follows. To guarantee the satisfaction of the predefined constraints, these are expressed in a range string i.e., chromosome, to the real values of process plans.

- Budget: Machine tool cost should be equal to or less than the predefined budget.

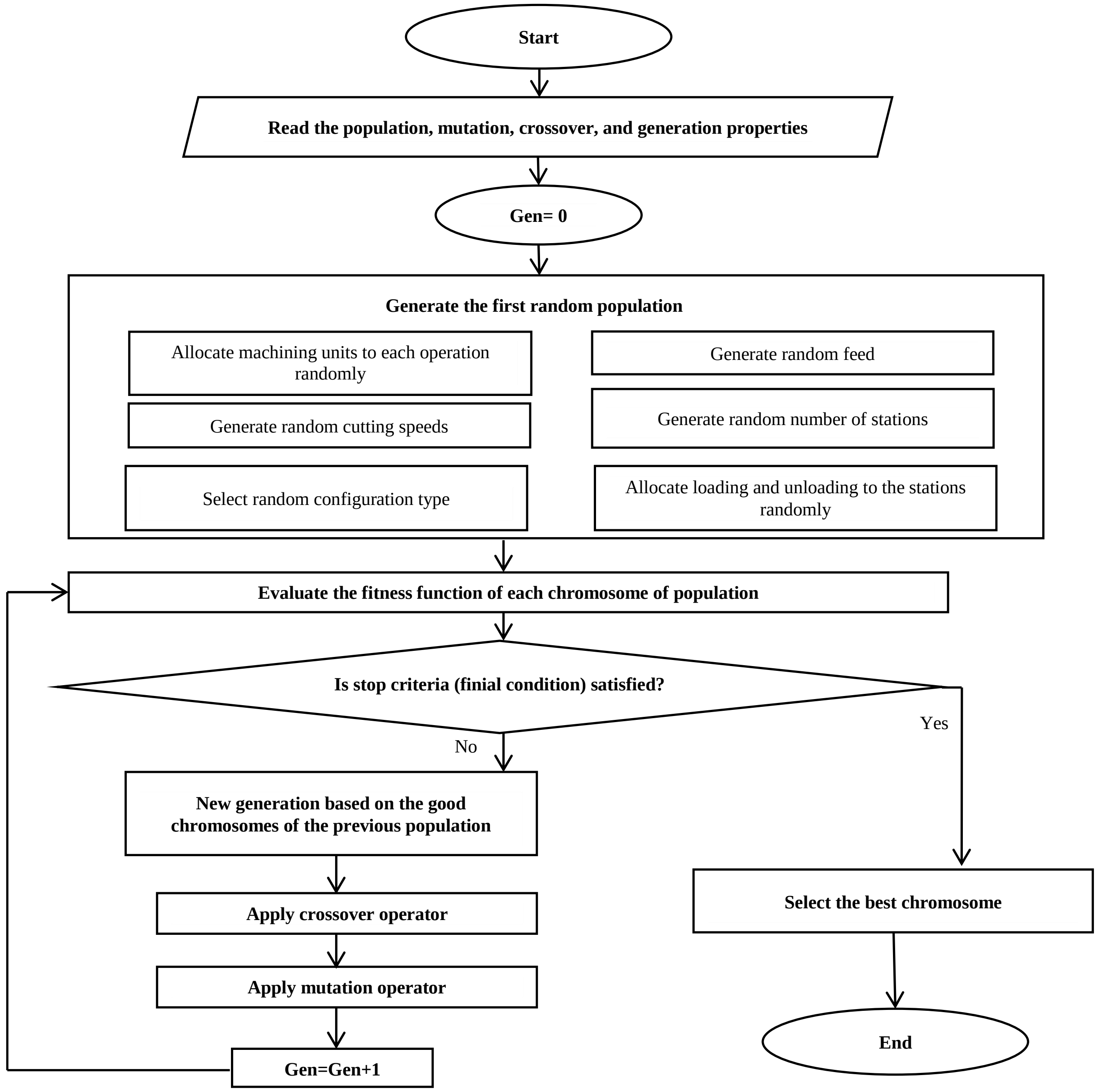

Fig.2. The flow chart of GA process steps for solving this problem.

of dependent variables between 0 and 1. Accordingly, decoding is required to translate the optimum solution

$$C_{mt} \leq B \tag{6}$$

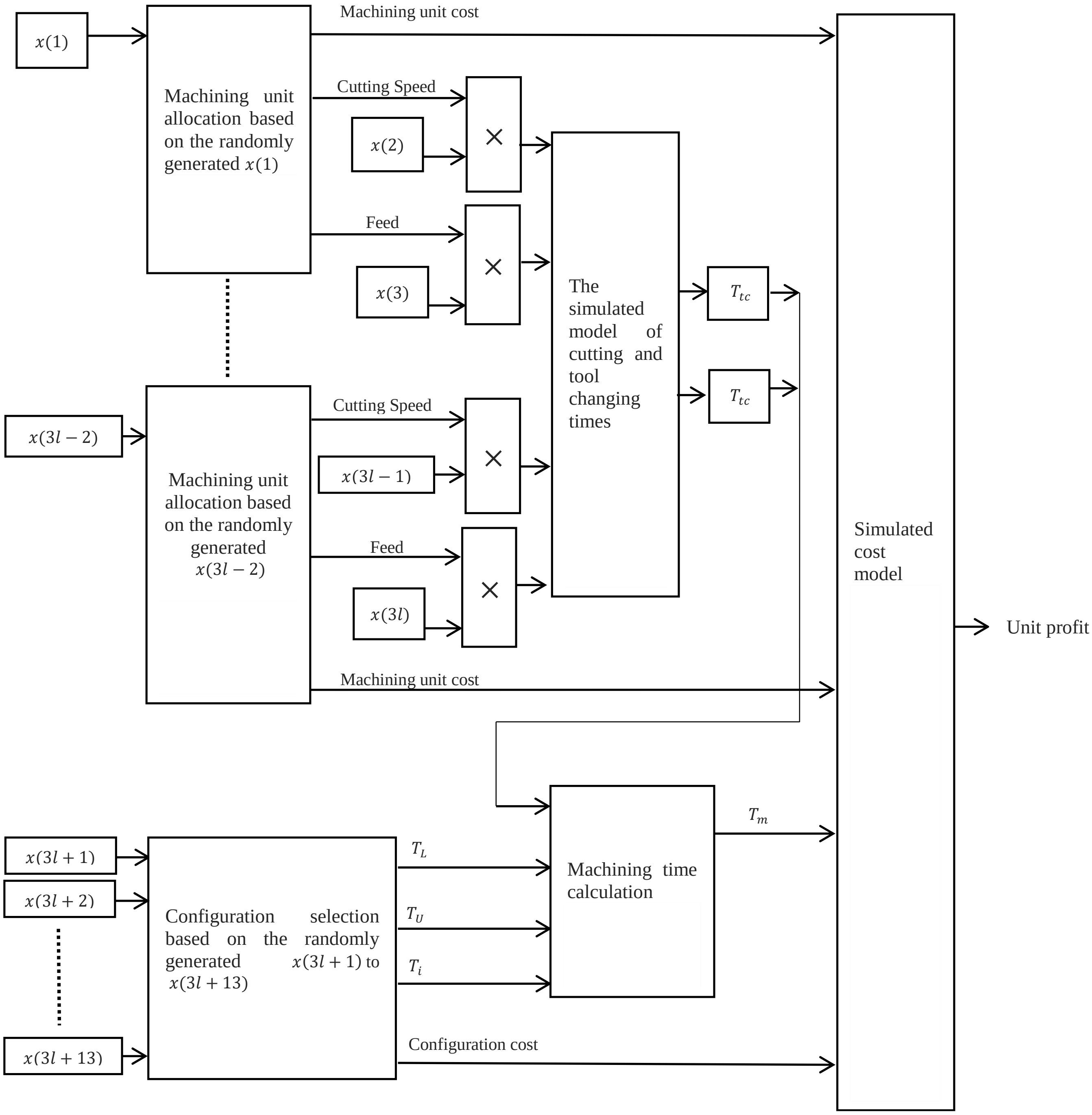

Fig.3. Schematic of simulation-based model: $\boldsymbol{x(1)}$ to $\boldsymbol{x(3l+13)}$, $\boldsymbol{l=1,\dots,L}$ are decision variables – where $\boldsymbol{l}$ defines the number of machining units – as below

– $x(1)$ and $x(3l-2)$ are used for machining unit allocation to each operation group.
– $x(2)$ and $x(3l-1)$ are used for generating a percentage of cutting speed of the selected machining unit.
– $x(3)$ and $x(3l)$ are used for generating a percentage of feed of the selected machining unit.
– $x(3l+1)$ is used for selecting configuration type.
– $x(3l+2)$ to $x(3l+13)$ are used for selecting number of stations and allocation of loading and unloading activities.

- Power: To drill an operation group, the required power can be estimated by considering number of holes/spindles, hole diameter, and part material [32]. Machining units which can provide equal or greater power are selected and utilized in the optimization process. Accordingly, different machining units may be feasible for drilling different operation groups.

$$P(N_{s\,k}, D_{h_k}, M_p) \le P_{m\,k} \tag{7}$$

$$\forall \quad k = 1, \dots, N_d \quad \& \quad m = 1, \dots, M$$

- Cutting speed: The allowable cutting speed range is recommended based on the tool type and part material [31]. Suhner general catalogue [32] provides an allowable spindle speed range of machining units, while cutting speed is a function of spindle speed and hole diameter [32]. Accordingly, the allowable range of cutting speeds for each machining unit may differ between operation groups.

$$v_{km\,min} \le v_{km} \le v_{km\,max} \tag{8}$$

$$\forall \quad k = 1, \dots, N_d \quad \& \quad m = 1, \dots, M$$

- Feed: Allowable feed can be defined based on the tool type, part material, and hole diameter [31]. Accordingly, the feed of each operation group is limited to the recommended feed range.

$$f_{k\,min} \le f_{km} \le f_{k\,max} \tag{9}$$

$$\forall \quad k = 1, \dots, N_d \quad \& \quad m = 1, \dots, M$$

2.1.4 GA operation options

The following options are defined for the GA.

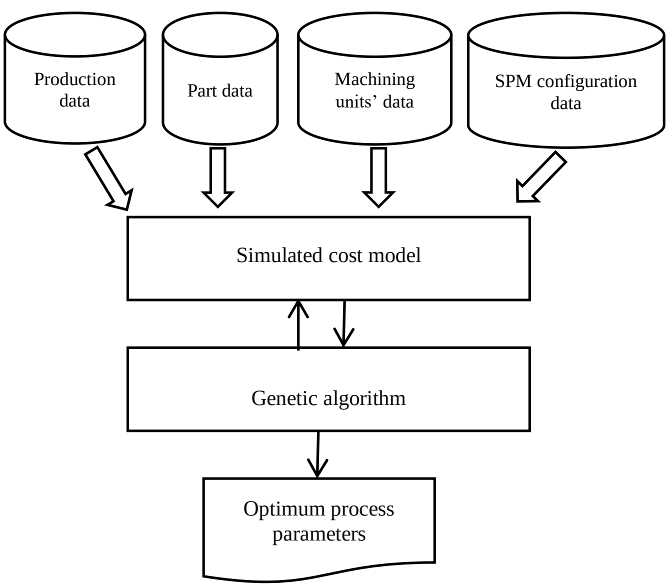

Fig.4. An integrated simulation-based GA model.

- Fitness function: This is explained in Section 2.1.2. It should be noted that penalty function is not used for this optimization process as variables have defined bounds.
- Mutation function: Adaptive feasible function is used to create new generations that have adapted from previous successful or unsuccessful generations while satisfying defined bounds and linear constraints.
- Crossover function: A two-point function is used to generate new chromosomes randomly by swapping parent strings from two points.
- Stopping criteria: stall generation was applied to stop the algorithm when the weighted average variation in the objective function value is less than defined function tolerance.

2.2. GA optimization process

GA is used to solve both constrained and unconstrained optimization problems by mimicking natural selection processes [30]. Fig. 2 illustrates how GA solves this optimization problem. The GA optimization process begins with a set of properties called a chromosome. A population of random chromosomes which are candidates for the optimization process are then evolved to become better chromosomes. Each candidate chromosome has a set of properties (its genotype) which can be altered by mutation or crossover operators. Chromosomes are usually indicated in binary format as strings of 0s and 1s; however, other encodings may be applied in the optimization model. The values of chromosomes in the current population are then evaluated using a fitness function and are ranked for the next generation. The process repeats until a predefined stopping criterion is met, as below:

– *Generations* specifies the maximum number of iterations the genetic algorithm performs.

– *Time limit* specifies the maximum time in seconds the genetic algorithm runs before stopping.

– *Fitness limit:* If the best fitness value is less than or equal to the value of the fitness limit, the algorithm stops.

– *Stall generations*: If the weighted average change in the fitness function value over stall generations is less than function tolerance, the algorithm stops.

– *Stall time limit*: If there is no improvement in the best fitness value for an interval of time in seconds specified by the stall time limit, the algorithm stops.

– *Function tolerance*: If the weighted average change in the fitness function value over stall generations is less than the Function tolerance, the algorithm stops.

3. Relationships between simulated cost model and GA process

This section explains how the GA optimization process is applied to the developed model. Firstly, the cost model is simulated using MATLAB/Simulink and is then integrated within the MATLAB/GA toolbox. Fig. 3 presents the schematic of the simulation-based model used for the GA optimization process. Fig. 4 indicates the connections between the simulation model, required data, and GA. First, part and production specifications, machining units, and SPM configuration data are entered into the simulation model for the optimization process. The optimization process then randomly selects the machining unit of each operation group, and the cutting speed and feed are then generated as a random percentage of the selected machining unit cutting speed and feed, respectively. Next, the number of stations and SPM layout type (rotary or sliding) are selected randomly, and machining units and loading and unloading activities are then allocated to each station. This process repeats until one chromosome with the maximum unit profit for the fitness function is obtained. This chromosome and the relevant fitness value are then taken to be the optimum solution.

4. Case study

This section illustrates a case study to validate the optimization model. The case study is throttle body and shows how the optimization results affect decision-making during the feasibility analysis stage (Fig.5). This part is made of Aluminium alloy 5083 and includes 14 holes with different properties. As shown in Table 1, similar holes on the same face are grouped into 8 main operation groups. A Simulink model is designed and created for the production of the throttle body before a connection is made between the Simulink model and the GA tool box. The optimization process is performed several times for different production volumes (demands), and the maximum result for each demand is utilized for further investigation. The optimization curve of Fig.6 shows the maximum unit profit which was obtained for different production volumes. The results are compared to the results of initial feasibility analysis which was achieved by Vafadar, Hayward and Tolouei-Rad [2]. These authors performed feasibility analysis based on the engineering knowledge and manufacturers' instructions. Fig.6 shows a comparison between the results of optimization and sensitivity analysis (SA) versus demand changes at feasibility analysis stage. SA is a part of feasibility analysis which investigates the effect of input parameters such as demand changes on the model's output.

Fig. 6 indicates that selecting optimum drilling process parameters, machining units, SPM layout type and configuration can significantly enhance unit profit. This issue considerably influences the results of decision-making process. This figure includes three areas requiring discussion: Area 1 shows that before performing the optimization process, the results of the initial solution for computer-numerical control machine (CNC) outperform that of SPM for lower demands. This is because the number of required SPMs is one and the costs are higher than the profit that is achieved by selling the products and salvage value of the machinery. In this range of demand, the number of required CNCs is also one. Since the sale profit for products produced by CNC is greater than the sale profit for products produced by SPM, the unit profit for products produced by CNC is greater than the unit profit for products produced by SPM. In this case, CNC is the appropriate choice for producing the throttle body. In contrast, the optimization results show that by selecting optimized decision variables, the SPM provides greater unit profits than the CNC machine and may be an appropriate choice for lower demand volumes. Specifically, the appropriate process parameter values decrease machining time, which is a major variable in machining, maintenance, overhead, and overhead costs. Furthermore, the selection of optimum machining units, layout type, loading and unloading station type, and number of work stations decreases capital investment cost. Accordingly, by decreasing the above-mentioned costs, the optimum variables boost unit profit (Eqs. 1 to 3).

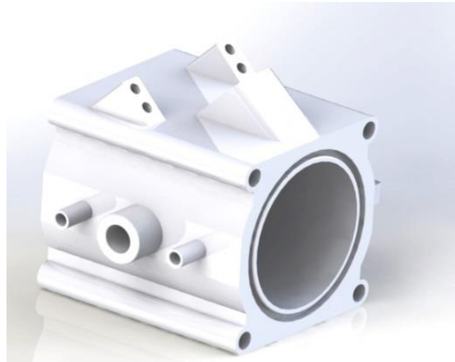

Fig.5. Throttle body downloaded from [34].

As indicated on Area 2 of Fig. 6, the results of this initial solution show that the unit profit of the SPM overtakes that of the CNC machine above 5,000 units. Since SPM and CNC drilling operations are parallel and sequential, respectively, the machining time of the CNC machine is higher than that of SPM. Accordingly, machining and maintenance costs (functions of machining time) increase at a considerable rate as demand increases. The interaction of machining costs, maintenance costs, and machining time makes decision-making difficult, because different factors have to be investigated.

Area 3 of Fig. 6 indicates a decline in the CNC curve. At this point another CNC machine is required due to increasing demand. The number of required machine tools is a function of demand [8]. Moreover, this area shows that the difference between the initial solution and the optimization results decreases as demand increases. The machine tool is approaching its demand capacity. Sales, and material, machining, maintenance, and overhead costs increase as they are the functions of demand. Increased demand does not influence the machine tool cost and salvage value which are fixed (Eqs. (1) and (2)). In addition, machining, maintenance, and overhead costs are functions of machining time. Since machining time of SPM is low, these costs are less sensitive than demand. Accordingly, when demand is high, the optimization process may not provide significant unit profit increases.

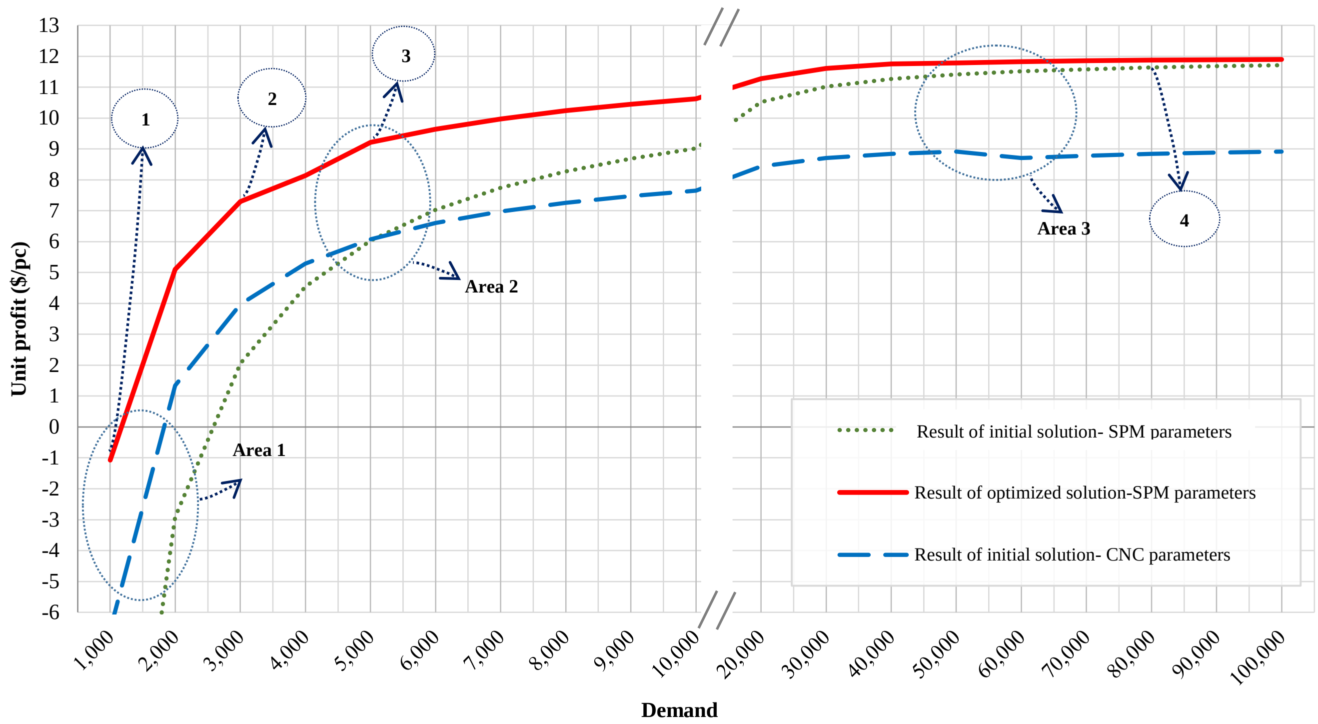

Fig.6. Results of sensitivity analysis and optimization for different demands.

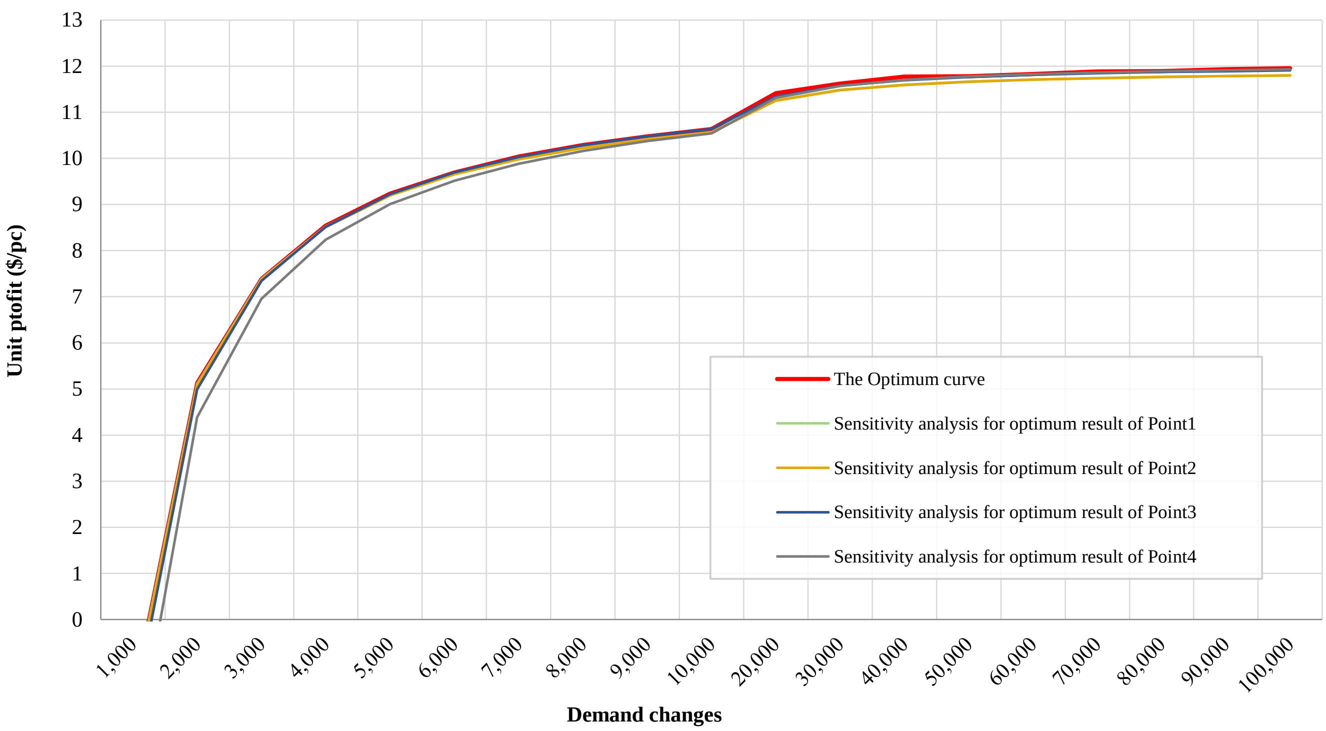

Fig.7. Results of sensitivity analysis for different optimum solutions which are shown in Fig.6.

Table 1 The properties of operation groups of the throttle body.

Operation group No.	Hole diameter (*mm*)	Length of hole (*mm*)	Number of holes
1	5.1	66	4
2	3.5	8	2
3	3.5	8	2
4	8	76	1
5	2	9	1
6	3.5	10	2
7	4.2	6	1
8	8.2	25	1

To investigate the effect of selecting optimum decision variables, four solutions from the optimization curve are selected, as indicated in Fig. 6. These solutions are selected to investigate the effect of the optimization process for different demands. The demands of these solutions are selected from the corresponding demand range, as below:

1) Solution 1 investigates low demands (≤ 1,000) in which CNC outperforms SPM in the initial analysis.
2) Solution 2 investigates low demands (> 1,000 and ≤ 5,000) before SPM overtakes CNC in the initial analysis.
3) Solution 3 investigates low demands (5000 ≤ and 20,000 <) where SPM overtakes CNC in the initial analysis.
4) Solutions 4 investigates large demands (>20,000).

Table 2 shows the results of optimization for these solutions. To better understand the economic behaviour; a sensitivity analysis is conducted for all these solutions, as shown in Fig. 7. This figure provides more insights, enabling manufacturers to select the optimum process parameters and configuration, based on market demands.

When producing this part, the results of solutions No. 1, 2, and 3 are very close to the optimum curve and each other, especially for lower demands (Fig. 7), whereas solution No.4 provides better results for higher demands. However, the manufacturers may choose other solutions based on production requirements. This optimization process applied in the feasibility analysis stage influences the profitability of the machine tool. This information aids companies in selecting an appropriate machine tool. For this purpose, the results of initial solution which is selected without the use of optimization was are compared with the optimized results for 100,000 units as presented in Fig. 8. For the given production requirements, solutions No.3 and 4 provide a greater unit profit. For the given production requirements, solutions No.1, 2, 3, and 4 provide a 1%, 1%, 1.7%, and 1.9% (respectively) increase in the unit profit compared to the initial solution. Improved selection methods by the designers may yield similar results; however the optimization algorithm effectively automates the process.

4.1. Identifying and investigating the effective decision variables

Table 3 shows feasible machining units which can be selected using the optimization model for each operation group. This table also represents the allowable range of feed and cutting speed for each machining unit. It is worth noting that, the range of cutting speed for each machining unit is defined by the operation group specifications [32]. The feed range is also defined based on the manufacturer’s catalogue [31].

Table 2 provides the optimized decision variables and non-optimum solution utilized for feasibility analysis. The non-optimum solution includes variables which are selected without optimization based on manufacturers’ recommendations [31, 32]. Generally, low cutting speed and high feed are selected to generate the maximum unit profit. Based on the required demand, different cutting speeds and feeds are selected. To investigate this, solution 2 where demand is 3,000 units is used. The following explanations justify the reasons for these different selections:

a) Machining time

Eq. (10) shows that machining time is a function of indexing, tool changing, and cutting times. Indexing time can be determined by the selected optimum indexing table and number of stations. Two other time parameters significantly influence the machining time and consequently machine tool, cutting, maintenance, machining, and overhead costs. Cutting and tool changing times are the function of some decision variables which are developed by Vafadar, Tolouei-Rad and Hayward [3], as explained below:

$$T_m = f(t_c,\ t_{tc},\ t_i) \tag{10}$$

$$t_c = f(\,v^{-1},\, f^{-1}) \tag{11}$$

$$t_{tc} = f(\,v^{-1},\, f^{-1}\,, v^{\frac{1}{n}}) \tag{12}$$

Table 2 Optimization results for the solutions shown in Fig. 6.

Solution No.		Initial parameters [1]	1	2	3	4
Demand (*units*)		1,000 to 950,000	1,000	3,000	5,000	80,000
Operation group No.1 [2, 3 & 4]	M	BEM 28	BEM 20	BEM 20	BEM 20	BEM 20
	V	90	73.90	75.82	69.2	87.1
	F	0.16	0.17	0.19	0.16	0.2
Operation group No.2 [2, 3 & 4]	M	BEM 12	BEM 12	BEM 12	BEM 12D	BEM 12D
	V	90	88.57	96.73	76.9	60.6
	F	0.13	0.16	0.18	0.18	0.17
Operation group No.3 [2, 3 & 4]	M	BEM 12	BEM 25H	BEM 12D	BEM 12D	BEM 20
	V	90	49.21	87.91	72.5	72.9
	F	0.13	0.18	0.19	0.19	0.2
Operation group No.4 [2, 3 & 4]	M	BEM 28	BEM 20	BEM 20	BEM 20	BEM 20
	V	90	90.24	74.20	88.2	77.2
	F	0.25	0.21	0.20	0.27	0.28
Operation group No.5 [2, 3 & 4]	M	BEM 3	BEM 12D	BEM 20	BEM 12D	BEM 20
	V	90	50.81	40.51	60.9	42.5
	F	0.1	0.16	0.14	0.15	0.16
Operation group No.6 [2, 3 & 4]	M	BEM 12	BEM 12D	BEM 20	BEM 12D	BEM 12D
	V	90	107.72	80.22	80.2	86.5
	F	0.13	0.15	0.12	0.12	0.18
Operation group No.7 [2, 3 & 4]	M	BEM 6	BEM 6D	BEM 6	BEM 6D	BEM 6D
	V	90	81.61	84.4	87.5	82
	F	0.16	0.18	0. 2	0.17	0.19
Operation group No.8 [2, 3 & 4]	M	BEM 28	BEM 20	BEM 20	BEM 20	BEM 20
	V	90	82.37	70.41	96.6	67.2
	F	0.25	0.3	0.26	0.28	0.29
Layout type		Rotary	Rotary	Rotary	Rotary	Rotary
Number of stations		6	6	6	6	6
L and U stations [5]		L-U	L-U	L-U	L-U	L-U

1: This solution was utilized for feasibility analysis before performing the optimization process.

2: M represents the selected machining unit type. BEM 3, BEM 6, BEM 6D, BEM 12, BEM 12D, BEM 12VC, BEM 20, BEM 28, and BEM 25H are different types of Suhner's machining units [32].

3: V represents the cutting speed which is measured in (*m/min*).

4: F represents the generated feed which is measured in (*mm/rev*).

5: L and U stations represent loading and unloading stations. If L-U is selected, loading and unloading activities are allocated to two stations. If L/U is selected, loading and unloading are allocated in one station.

Table 3 Cutting speeds and feed ranges of the feasible machining units [1] for each operation group in the optimization problem

Operation group No.	Machining unit type [2]	Min allowable cutting speed [3]	Max allowable cutting speed [3]	Feed range [4]
1	BEM20	64.1	128.1	0- 0.2
	BEM28	45.0	90.0	0- 0.2
	BEM25H	64.1	128.1	0- 0.2
2	BEM12	54.9	109.9	0- 0.2
	BEM12D	54.9	109.9	0- 0.2
	BEM12VC	55	109.9	0- 0.2
	BEM20	43.9	87.9	0- 0.2
	BEM28	19.1	38.2	0- 0.2
	BEM25H	43.9	87.9	0- 0.2
3	BEM12	54.9	109.9	0- 0.2
	BEM12D	54.9	109.9	0- 0.2
	BEM12VC	55	109.9	0- 0.2
	BEM20	43.9	87.9	0- 0.2
	BEM28	19.1	38.2	0- 0.2
	BEM25H	43.9	87.92	0- 0.2
4	BEM20	70.0	140.0	0- 0.3
	BEM28	45.0	90.0	0- 0.3
	BEM25H	70.0	140.0	0- 0.3
5	BEM3	79.1	113.0	0- 0.2
	BEM6	43.9	62.8	0- 0.2
	BEM6D	61.5	87.9	0- 0.2
	BEM12	43.9	62.8	0- 0.2
	BEM12D	43.9	62.8	0- 0.2
	BEM12VC	43.9	62.8	0- 0.2
	BEM20	35.1	50.24	0- 0.2
	BEM28	10.9	21.8	0- 0.2
	BEM25H	35.1	50.24	0- 0.2
6	BEM12	76.9	109.9	0- 0.2
	BEM12D	76.9	109.9	0- 0.2
	BEM12VC	76.9	109.9	0- 0.2
	BEM20	61.5	87.9	0- 0.2
	BEM28	26.7	38.2	0- 0.2
	BEM25H	61.5	87.9	0- 0.2
7	BEM6	79.1	131.8	0- 0.2
	BEM6D	84.0	140	0- 0.2
	BEM12	79.1	131.8	0- 0.2
	BEM12D	79.1	131.8	0- 0.2
	BEM12VC	79.1	131.8	0- 0.2
	BEM20	63.3	105.5	0- 0.2
	BEM28	27.5	45.8	0- 0.2
	BEM25H	63.3	105.5	0- 0.2
8	BEM20	70.0	140.0	0- 0.3
	BEM28	44.8	89.6	0- 0.3
	BEM25H	70.0	140.0	0- 0.3

1: Feasible machining units are selected based on the method which is proposed by Vafadar, Tolouei-Rad, Hayward and Abhary [4]. This method considers part properties, SPM component characteristics, and production requirement for the selection of feasible components.

2: Machining units utilized in the optimization model are MONO masters taken from Suhner general catalogue [32].

3: Cutting speed range of each operation group for machining units extracted from [32].

4: Feed range recommended in the manufacturers' catalogues [31].

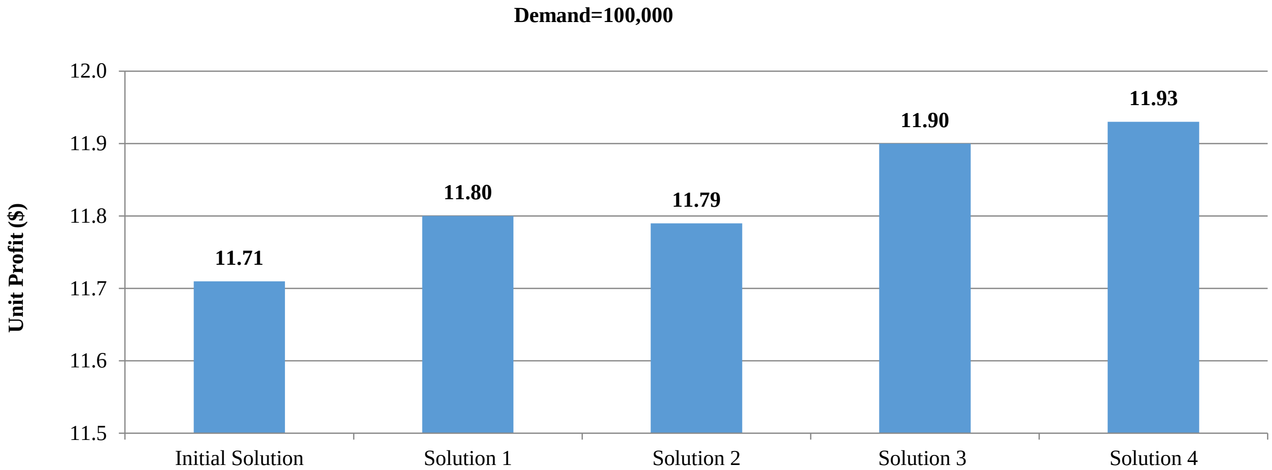

Fig.8. Comparison between the results of initial solution and the optimum solutions indicated in Fig.6 and the solution provided used by Vafadar, Hayward, and Tolouei-Rad [2, 3].

From these three equations it can be concluded that the effect of cutting speed changes on the tool changing time is more than that of cutting time. As Eq. (12) shows, tool changing time is a function of the Taylor exponent which is determined by the material for the part and cutting tool [33]. The throttle body material is aluminum alloy and the selected cutting tool material is high speed steel. The Taylor exponent is therefore 0.125 [33]. Accordingly, decreasing the cutting time results in a significant reduction in the tool changing time, the cutting time increases slightly, and consequently machining time decreases.

Eqs. 11 and 12 also show that by increasing the feed, cutting time and tool changing times decrease and consequently costs decrease. Therefore, the optimization process generates the lowest possible cutting speed and the highest possible feed to maximize unit profit.

b) Tooling cost

Tooling cost is another important cost which significantly influences unit profit. The following equation shows how feed and cutting speed influence the tooling cost [3]:

$$C_t = f(\, v^{-1},\, f^{-1}, v^{\frac{1}{n}}) \qquad (13)$$

From this equation it can be concluded that lower cutting speeds and higher feeds reduce the tooling cost and increase unit profit. The effects of cutting speed and feed changes for operation group No.4 on unit profit and tooling cost are shown in Figs. 9 and 10, respectively. For this case study, operation group No. 4 is a bottleneck which has the highest cutting time of all operation groups. An operation group which produces the bottleneck time significantly affects costs and consequently unit profit. Accordingly, these figures focus on the bottleneck operation group among the studied solutions. It can be seen that increasing the cutting speed boosts costs, especially the tooling cost. Indeed, increasing the cutting speed boosts tool consumption and tool changing time considerably, and as a result the unit profit decreases. Fig. 10 shows that increasing the feed slightly decreases the tooling cost and also has a significant effect on some other costs. Figs. 9 and 10 provide the behaviour of some other costs such as overhead, maintenance, and machining versus cutting speed and feed changes, which are explained in the following section.

c) Machining cost

Figs. 9 and 10 indicate that machining cost is an important cost which significantly influences unit profit. This cost is a function of machining time. As explained in Section 4.1(a), decreasing cutting speed and increasing feed decrease machining time. Therefore, machining cost decreases, and consequently the unit profit increases. It can also be seen that decreasing cutting speed and increasing feed slightly reduces some costs, such as maintenance and overhead costs.

d) Machine tool cost

The equation below shows that the machine tool cost is a function of machining unit and indexing table costs and machining time [3].

$$C_{mt} = f(\, C_{mu}\,,\; C_{it}\,, Roundup(k_{14}\, T_m)) \qquad (14)$$

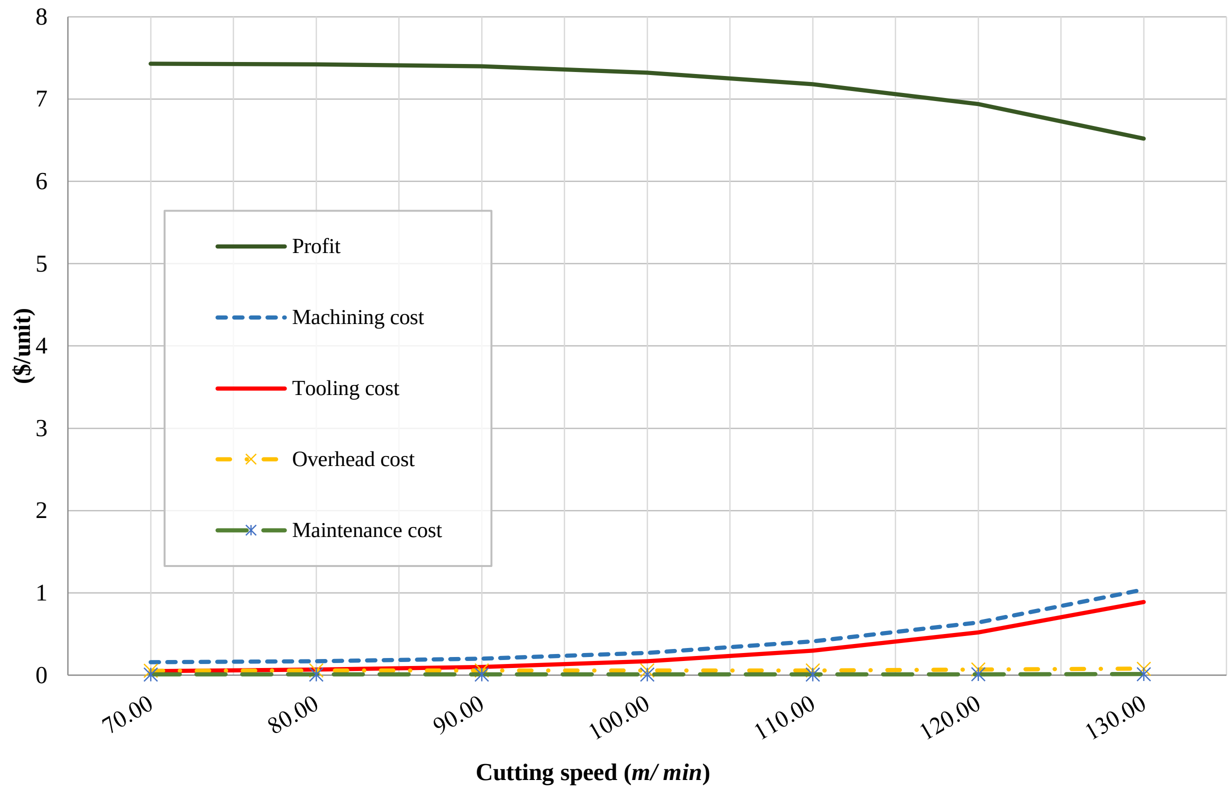

Fig.9. The effect of cutting speed changes for operation group No.4 of solution 2.

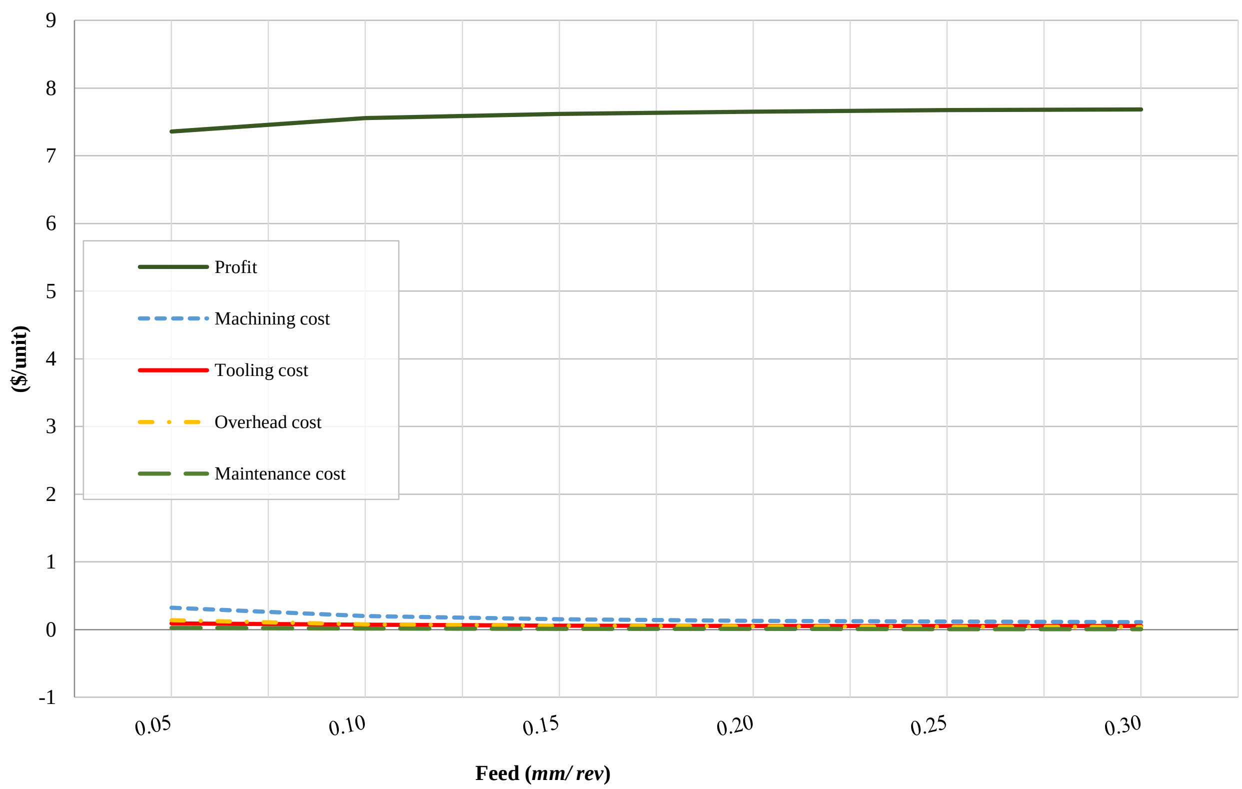

Fig.10. The effect of feed changes for operation group No.4 of solution 2.

Indexing table cost is determined by the number of stations, which is determined by the allocation of machining units and loading and unloading activities to the stations. If the optimization model assigns loading and unloading to the same station, the number of stations will be reduced and consequently the cost will be reduced. But in this case, the loading and unloading will be allocated to one station. Accordingly, this station will be considered as a bottleneck. Moreover, in this model, manual loading and unloading is considered, so the bottleneck time has a high value and therefore, machining time and costs will increase. Accordingly, the optimization model determines the machining units and indexing table which have the lowest possible cost while keeping the machining time low.

5. Conclusion

This paper discussed optimization for determining feasible SPM layouts and choosing process parameters that lead to a maximum unit profit. To do so, a heuristic method was selected to consider all these variables for varying production volumes. The appropriate selection of an SPM configuration and process parameters may influence the results of the decision-making process. In reviewing the application of GA technique for the optimization of process planning and machine tool configuration problems, this study focuses on the feasibility analysis of utilizing SPM versus other available alternatives, an approach that has not been adequately addressed by other researchers. This research makes a key contribution to the machine tool selection problem at an early stage in the decision-making process.

A cost model which dealt with time and cost factors for evaluating the performance of SPM and other machine tools was presented in order to design the optimization model. An objective function was developed for the optimization process and the decision variables were identified along with boundaries and constraints. The production part was simulated by Simulink/MATLAB and was integrated into the GA technique to perform the optimization.

The proposed optimization model has been successfully applied to the case study described in this paper. The results have been evaluated and discussed with respect to two main areas. The first relates to the comparison between the results of optimization and the initial feasibility analysis, before performing optimization process. The results show that selecting appropriate SPM configuration and process parameters can significantly influence machine tool performance, and this has an effect on the decisions taken during the early stages of investment in a machine tool. The second area relates to investigating the results of the optimization output and identifying the critical factors which influence SPM performance. The research found that the bottleneck operation group, tooling costs and machining time are critical factors which are influenced by decision variable values.

This study generates ideas for future work. The first objective could be to assess other factors such as labour and overhead rates. The second could be applying a GA-based method and considering uncertainty in the context of the dynamic optimization problem. Another consideration could be comparing a GA approach with other emerging optimization methods. Applying the proposed objectives will help companies to make a relatively quick and accurate decisions by selecting the near optimal SPM and process parameters that will facilitate choosing the right machine tool in the preliminary stages of the investment phase.

Acknowledgement

The authors would like to thank Dr Helen Renwick for her useful writing comments to improve the paper.

Nomenclature

a	Availability (%)
B	Budget (*$*)
$C_{downtime}$	Cost of annual production losses (*$/year*)
C_{it}	All costs related to indexing table and accessories (*$*)
$C_{machining}$	Annual machining cost (*$/year*)
$C_{maintenance}$	Annual maintenance cost (*$/year*)
$C_{material}$	Annual material cost (*$/year*)
C_{mt}	Machine tool cost (*$*)
C_{mu}	Cost of machining units (*$*)
$C_{overhead}$	Annual overhead cost (*$/year*)
C_{total}	Total life cycle production cost (*$*)
D	Annual demand
D_h	Hole diameter (*mm*)
f	Feed (*mm/rev*)
H	Average working hours (*h/year*)
i	Annual interest rate
j	Year of operation or production
K_1 to K_{14}	Constants
k	Index of drilling heads/ operation groups
L	Number of machining units
l	Index of machining units
M	Number of available machine tools
M_p	Part material
m	Index of machining unit
N_d	Number of drilling heads/operation groups
N_s	Number of spindles per drilling head
n	Number of variables
P_m	Required power to drill the operation group (*kW*)
q	Scrap rate (%)
S	Salvage value (*$*)
S_p	Sale price of the product (*$*)
T_c	Total cutting time (*min*)
T_i	Indexing/Sliding time (*min*)
T_L	Loading time (*min*)
$T_{L/U}$	Loading and unloading time (*min*)
T_U	Unloading time (*min*)

T_m	Machining/Cycle time per year (*min*)
T_{mo}	Maintenance time (*min*)
T_s	Setup time (*min*)
T_{tc}	Total tool changing time (*min*)
t	Number of production years
t_c	Cutting time for each drilling head (*min*)
t_i	Indexing time (*min*)
t_{tc}	Tool changing time for each spindle head tool (*min*)
v	Cutting speed (*mm/min*)

References

[1] A.I. Shabaka, H.A. ElMaraghy, A model for generating optimal process plans in RMS, International Journal of Computer Integrated Manufacturing, 21 (2008) 180-194.
[2] A. Vafadar, K. Hayward, M. Tolouei-Rad, Sensitivity analysis for justification of utilising special purpose machine tools in the presence of uncertain parameters, International Journal of Production Research, 55 (2017) 3842-3861.
[3] A. Vafadar, M. Tolouei-Rad, K. Hayward, New cost model for feasibility analysis of utilising special purpose machine tools, International Journal of Production Research, 54 (2016) 7330-7344.
[4] A. Vafadar, M. Tolouei-Rad, K. Hayward, K. Abhary, Technical feasibility analysis of utilizing special purpose machine tools, J Manuf Syst 39, (2016) 53-62.
[5] A. Vafadar, M. Tolouei-Rad, K. Hayward, Evaluation of the effect of product demand uncertainty on manufacturing system selection in: 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017 Elsevier, Modena, Italy, 2017.
[6] A. Vafadar, M. Tolouei-Rad, K. Hayward, K. Abhary, Technical feasibility analysis of utilizing special purpose machine tools, Journal of Manufacturing Systems, 39 (2016) 53-62.
[7] M. Tolouei-Rad, S. Zolfaghari, Productivity improvement using Special-Purpose Modular machine tools, International Journal of Manufacturing Research, 4 (2009) 219-235.
[8] A. Vafadar, M. Tolouei-Rad, K. Hayward, New cost model for feasibility analysis of utilising special purpose machine tools, International Journal of Production Research, (2016) 1-15.
[9] H. Son, H.-J. Choi, H.W. Park, Design and dynamic analysis of an arch-type desktop reconfigurable machine, International Journal of Machine Tools and Manufacture, 50 (2010) 575-584.
[10] Y.-M. Moon, S. Kota, Generalized Kinematic Modeling of Reconfigurable Machine Tools, Journal of Mechanical Design, 124 (2002) 47.
[11] H. Azulay, J.K. Mills, B. Benhabib, A Multi-Tier Design Methodology for Reconfigurable Milling Machines, Journal of Manufacturing Science and Engineering, 136 (2014) 041007.
[12] Y. Koren, M. Shpitalni, Design of reconfigurable manufacturing systems, Journal of Manufacturing Systems, 29 (2010) 130-141.
[13] X. Xu, L. Wang, S.T. Newman, Computer-aided process planning–A critical review of recent developments and future trends, International Journal of Computer Integrated Manufacturing, 24 (2011) 1-31.
[14] S. Li, Y. Liu, Y. Li, R.G. Landers, L. Tang, Process planning optimization for parallel drilling of blind holes using a two phase genetic algorithm, Journal of Intelligent Manufacturing, 24 (2012) 791-804.
[15] F. Cus, J. Balic, Optimization of cutting process by GA approach, Robotics and Computer-Integrated Manufacturing, 19 (2003) 113-121.
[16] S. Kafashi, Integrated setup planning and operation sequencing (ISOS) using genetic algorithm, The International Journal of Advanced Manufacturing Technology, 56 (2011) 589-600.
[17] H. Marri, A. Gunasekaran, R. Grieve, Computer-aided process planning: a state of art, The International Journal of Advanced Manufacturing Technology, 14 (1998) 261-268.
[18] H.-T. Nguyen, S.Z.M. Dawal, Y. Nukman, H. Aoyama, A hybrid approach for fuzzy multi-attribute decision making in machine tool selection with consideration of the interactions of attributes, Expert Systems with Applications, 41 (2014) 3078-3090.
[19] B. Yilmaz, M. Dağdeviren, A combined approach for equipment selection: F-PROMETHEE method and zero–one goal programming, Expert Systems with Applications, 38 (2011) 11641-11650.
[20] O. Durán, J. Aguilo, Computer-aided machine-tool selection based on a Fuzzy-AHP approach, Expert Systems with Applications, 34 (2008) 1787-1794.
[21] Y. Tansel İç, M. Yurdakul, B. Dengiz, Development of a decision support system for robot selection, Robotics and Computer-Integrated Manufacturing, 29 (2013) 142-157.
[22] J.B. Dai, N.K.S. Lee, Economic feasibility analysis of flexible material handling systems: A case study in the apparel industry, International Journal of Production Economics, 136 (2012) 28-36.
[23] G. Quintana, J. Ciurana, Cost estimation support tool for vertical high speed machines based on product characteristics and productivity requirements, International Journal of Production Economics, 134 (2011) 188-195.
[24] N. Yusup, A.M. Zain, S.Z.M. Hashim, Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007–2011), Expert Systems with Applications, 39 (2012) 9909-9927.
[25] Y.-C. Wang, Y.-C. Chiu, Y.-P. Hung, Optimization of multi-task turning operations under minimal tool waste consideration, Robotics and Computer-Integrated Manufacturing, 27 (2011) 674-680.
[26] A. Vafadar, Thesis Title, in, Iran University of Science and Technology, 2010.
[27] A.M.A. Youssef, H.A. ElMaraghy, Modelling and optimization of multiple-aspect RMS configurations, International Journal of Production Research, 44 (2006) 4929-4958.

[28] E.U. Guldogan, An integrated approach to machine selection and operation allocation problem, The International Journal of Advanced Manufacturing Technology, 55 (2010) 797-805.
[29] A. Chaube, L. Benyoucef, M.K. Tiwari, An adapted NSGA-2 algorithm based dynamic process plan generation for a reconfigurable manufacturing system, Journal of Intelligent Manufacturing, 23 (2012) 1141-1155.
[30] A.M. Zain, H. Haron, S. Sharif, Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process, Expert Systems with Applications, 37 (2010) 4650-4659.
[31] HSS Forum, Think reliability, Think HSS, in, 2014.
[32] Suhner general catalogue, Automation Expert, in, http://www.suhner-automation-expert.com/site/index.cfm?id_art=113098&actMenuItemID=52595&vsprache=EN, Switzerland, 2012.
[33] M.P. Groover, Automation, production systems, and computer-integrated manufacturing, 4th ed., Prentice Hall Press, 2014.
[34] D. Stamatopoulos, NA inlet manifold and throttle bodies, in, https://grabcad.com/library/na-inlet-manifold-and-throttle-bodies, 2012.