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ORIGINAL ARTICLE

Optimization of machining economics and energy consumption in face milling operations

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Abstract
Metal cutting (or machining) is one important aspect of the manufacturing system. Selecting optimal cutting conditions for machining is then a crucial process planning task for manufacturing. Traditionally, solving such machining problems was only focused on economic objectives such as maximizing profit or minimizing production time requirement. In the recent decade, however, minimizing energy consumption in manufacturing processes has attracted increased attention due to increasing energy costs and concern with greenhouse gas emissions. Energy loss could be avoided by carefully selecting cutting parameters. This paper develops a multi-objective mathematical model to minimize unit production costs along with energy consumption for face milling operations. In addition, an evolutionary strategy (ES)-based optimization approach is used to identify optimal cutting conditions for the proposed model.

Keywords Machining economics · Energy consumption · Face milling · Evolutionary strategy

Nomenclature

A	Cross-sectional area of uncut chip
a_d	Approach distance of the tool (mm)
a_p	Depth of cut (mm)
a_{pri}, a_{pf}	Depth of cut for rough and finish passes (mm)
$a_{pr,\ max}$, $a_{pf,\ max}$	Maximum depth of cut for rough and finish operations (mm)
$a_{pr,\ min}$, $a_{pf,\ min}$	Minimum depth of cut for rough and Finish operations (mm)
a_T	Total depth of cut (mm)
B	Width of work piece (mm)
C_i	Machine idle cost ($)
C_m	Machining cost ($)
C_r	Tool replacement cost ($)
C_t	Tool cost ($)
C_p	Machine preparation cost ($)
C_{ri}, C_f	Cost of machining for roughing and finish passes ($)
C_{mw}	Machinability of work materials
C_w	Cutting tool wear factor
C_v, m	Constants of tool-life equation
D	Cutter diameter (mm)
e_1, e_2, e_3	Constraint on parameter relations
F_i	Cutting force for ith passes (N)
F_{max}	Maximum cutting force (N)
f_z, f_{zri}, f_{zf}	Feed for rough and finish passes (mm/tooth)
$f_{z,\ max}$, $f_{z,\ min}$	Maximum and minimum feed (mm/tooth)
h_1, h_2	Tool return time (min/mm) and tool advance/return time (min)
k_0	Overhead cost ($/min)
k_t	Cost of cutting edge of tool material ($/cutting edge)
k_r	Cutting edge angle
k_1, k_2, k_3	Constants of specific energy consumption equation
L	Length of work piece (mm)
L_r, L_f	Cutting travel length for rough and finish passes (mm)

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MRR_i	Material removal rate for ith passes (mm^3/s)
N_{ri}, N_f	Spindle speed for rough and finish passes (rpm/s)
N_{max}	Maximum spindle speed (rpm/s)
np	Number of passes (npass-1 roughing and one finish)
P_i	Power in for ith passes (kW)
P_{max}	Maximum power (kW)
R_{ari}	Surface mean roughness (μm)
R_{ari}, R_{af}	Surface mean roughness for rough and finish passes (μm)
$R_{ar,\ max}$, $R_{af,\ max}$	Maximum surface mean roughness rough and finish passes (μm)
r_e	Nose radius of cutting edge of cutter (mm)
SEC	Total specific energy consumption (J/mm^3)
T_i	Tool-life in cutting (min)
T_R	Tool replacement life value (min)
t_e	Tool-exchange time (min/cutting edge)
t_p	Preparation time (min/piece)
t_i	Idle tool motion time (min)
t_m	Machining time (min)
t_{mri}	Machining time for rough passes (min)
t_{mf}	Machining time for finish passes (min)
UC_T	Unit product total cost of machining($)
V, V_{ri}, V_f	Cutting speed/cutting speed for rough and finish passes (m/min)
V_{max}, V_{min}	Maximum and minimum cutting speed (m/min)
Z_c	Number of inserts in the cut
z	Number of cutter tooth
σ	Tensile strength of work materials (N/mm^2)
ε	Cutter extra-travel (mm)

1 Introduction

1.1 Background

Correctly determining the proper values for machining parameters such as number of passes, cutting speed, feed rate, and depth of cut for each pass can significantly influence production efficiency, product quality, and manufacturing costs. The shop floor process planner selects the machining parameters based on professional experience or published guidelines with consideration of part geometry and material, cutting tool material and tool life, machine power limitations, cutting force, temperature, and required surface finish. These considerations create difficult machining economics problems and, in practice, the solution set does not typically produce optimal results. Machining problems are typically optimized in terms of either the minimum production time or the maximum production profit as the objective function subject to several practical constraints. Several studies have previously focused on solving machining economics problems.

However, manufacturers are increasingly concerned about the environmental impact of their operations [1]. Manufacturing is an energy-intensive industry, accounting for 31% of total primary energy use, and is responsible for 36% of total carbon dioxide emissions [2]. Firms need to consider energy efficiency performance alongside other important performance metrics such as costs, flexibility, delivery time, and product quality. In many investment goods, energy efficient production is seen as a potential selling point for customers. Many approaches have been proposed to increase manufacturing energy efficiency especially in terms of the use of machine tools. Gutowski et al. [3] found the most important variable for estimating energy requirements for machining is the process rate which is material removal rate (MRR).

This paper is organized as follows. Section 1 reviews the literature regarding the optimization of process parameters for milling operations and regarding energy efficiency for metal cutting processes. Section 2 presents the proposed mathematical model and the machining constraints. Section 3 describes an evolutionary strategy-based approach for solving the proposed model. Section 4 presents and discusses the computational results. Finally, Section 5 presents conclusions and directions for future research.

1.2 Machining economics for face milling operations

Many studies have examined problems related to machining parameters for turning processes [4]. Relatively, less work has focused on optimizing multi-point cutting operations such as milling. Shunmugam et al. [5] developed a model to minimize production per-unit costs in face milling operations (Fig. 1) and proposed a two-stage approach involving the genetic algorithm (GA). Several studies then extended this model, with An and Chen [6] proposing a two-stage approach using integer programming (IP). These two-stage optimization approaches entailed significant computational loading for additional cutting passes. Conceição et al. [7] proposed a genetic algorithm to solve the same problem, but their solution did not satisfy the constraint imposed by specific surface roughness requirements. Zarei et al. [8] proposed a harmony search algorithm which converged to an optimum solution with higher accuracy and efficiency than GA. Yang et al. [9] solved Shunmugam's model while considering additional objectives, minimizing production time and costs, while maximizing profit (Table 1). Their proposed particle swarm optimization method significantly improved on results from previous studies.

In verifying and validating the solutions provided in the above studies, we found several common misconceptions and errors, including:

Table 1 Misconceptions and errors for previous studies on Shunmugam's case

Authors	Year	Approach	Cost ($)	Misconceptions/errors
Shunmugam et al.	2000	GA	2.0086	a b
An and Chen	2003	IP	1.8523	Not provided
Conceição et al.	2009	GA	1.8658	b e
Zarei et al.	2009	HAS	1.7689	c f
Zarei et al.	2009	GA	1.7879	d f
Saha	2009	GA	1.7615	f
Yang.et al	2011	PSO	1.6998	c
Yang.et al	2011	F-MOPSO	1.7	c

a. Cutting speed should be lower in roughing than that in finishing.
b. Feed in finishing should be set lower than feed in roughing.
c. The best solution found violates the power constraint.
d. The best solution found violates the pre-determined tool life length.
e. The best solution found cannot achieve the surface roughness required.
f. The unit cost was incorrectly calculated.

1.3 Energy consumption for machining

Machining operations use electric machine tools, and the minimum power required for machining can be estimated using cutting force and cutting speed. Estimated cutting power and the machining time can then be used to calculate energy demand for machining operations. However, this energy demand only accounts for a small share of the total energy for the machine tool system to complete required material removal processes. A machine tool consists of a frame, guiding system, spindle, cooling system, and control units. During machining operations, machine tool system power consumption changes dynamically [10]. Gutowski et al. [3] defined the specific energy consumption, SEC, as the energy consumption required for the machine tool to remove 1 cm^3 of material. SEC is thus used to indicate the energy efficiency of a machine tool or manufacturing process. The SEC of Gutowski et al. was defined as follows:

$$\mathrm{SEC} = \frac{P_{\text{fixed}}}{\mathrm{MRR}} + k \tag{1}$$

This model indicates that the fixed power P_{fixed} is anticipated as a constant and a material- and process-specific energy constant k. The only variable of this energy model is MRR. If the P_{fixed} and material- and process-specific energy constant k are known, this SEC model allows a product designer to estimate the manufacturing energy consumption for producing the part without needing to measure power demand directly from the machine tool during production.

Gutowski's model was later confirmed by Diaz et al. [11] conducting several experiments on milling machine tools to show relationships among energy consumed, material removal rate, and power demand. Mori et al. [12] investigated the impact of various machining parameters on energy consumption for drilling, face milling, and end milling operations. The results showed that machining energy can be conserved by setting cutting conditions to maximize MRR without compromising tool life and surface finish. This also verified the Gutowski model. Kianinejad et al. [13] compared newer and outdated milling machines in terms of energy consumption and machining efficiency, finding that the SEC of the outdated machine is much lower because of its relatively low removal rate.

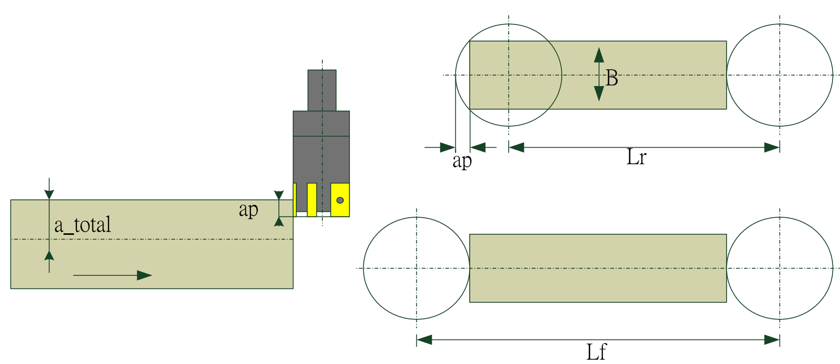

Fig. 1 Rouging and finishing scheme for face milling operation

Li and Kara [14] pointed that previous studies have largely overlooked energy consumption for numerous auxiliary functions. They presented an empirical model for energy consumption prediction of a CNC machine tool performing a turning operation. Kara and Li [15] later extended this study to investigate the relationship between energy consumption and process variables for various CNC turning and milling machines under dry and wet cutting conditions. Li et al. [16] conducted similar experiments for a grinding machine. This energy consumption model was then improved as a function of MRR and spindle speed for material removal processes by Li et al. [17, 18].

$$\mathrm{SEC} = \; k_1 + k_2 \frac{n}{\mathrm{MRR}} + k_3 \frac{1}{\mathrm{MRR}} \tag{2}$$

They proved that the new model could provide more accurate estimates of energy consumption than the model only considering MRR for a milling machine tool case. The best way to obtain the coefficients of this improved SEC model for a machine tool for material removal is to carry out experiments and analyze the results.

2 Modeling the problem

The mathematical machining model in this study is modified from that originally proposed by Shunmugam et al. [5]. A face milling operation is performed on the top surface of a rectangular workpart with several rough cuts and a finish cut. Equations (3) and (4) respectively present the objectives of minimizing the production cost per unit and the SEC. Equation (3) consists of eight terms. The first four terms relate to rough milling and the last four terms relate to finish milling. For rough milling, the first term refers to the machining cost, the second term refers to the tool changing cost, the third term refers to the tool cost, while the fourth term relates to the cost involved in idle motion of the tool. Equation (4) is based on the model of Li et al. [17]. Equation (4) consists of six terms. The first three terms relate to rough milling and the last three terms relate to finish milling. k_1 is the specific energy in face milling operations, k_2 is the specific coefficient of spindle motor, and k_3 is the constant coefficient of machine tool.

These two objectives must be optimized simultaneously.

Objective functions

$$\begin{aligned}
\min \mathrm{UC_T} = {} & k_0 \times \left(\sum_{i=1}^{np-1} \frac{DL_r}{1000\, V_{ri} f_{Zri} z} \right) + k_0 \times \left[\sum_{i=1}^{np-1} \left(\frac{z t_e}{T_R} \times \frac{DL_r}{1000\, V_{ri} f_{Zri} z} \right) \right] \\
& + \sum_{i=1}^{np-1} \left(\frac{z k_t}{T_R} \times \frac{DL_r}{1000\, V_{ri} f_{Zri} z} \right) + k_0 \times \left[\sum_{i=1}^{np-1} (h_1 L_r + h_2) \right] + k_0 \times \left(\frac{DL_f}{1000^{*}\, V_f f_{Zf} z} \right) \\
& + k_0 \times \left(\frac{z t_e}{T_R} \times \frac{DL_f}{1000\, V_f f_{Zf} z} \right) + \left(\frac{z k_t}{T_R} \times \frac{DL_f}{1000\, V_f f_{Zf} z} \right) + k_0 \times (h_1 L_f + h_2) + k_0 t_p
\end{aligned} \tag{3}$$

$$\begin{aligned}
\min\ \mathrm{SEC} = {} & \sum_{i=1}^{np-1} k_1 + \sum_{i=1}^{np-1} \left(k_2 \times \frac{1}{a_{pri} \times B \times f_{zri} \times z} \right) + \sum_{i=1}^{np-1} \left(k_3 \times \frac{1}{a_{pri} \times B \times f_{zri} \times z \times N_{ri}} \right) \\
& + k_1 + \left(k_2 \times \frac{1}{a_{pf} \times B \times f_{zf} \times z} \right) + \left(k_3 \times \frac{1}{a_{pf} \times B \times f_{zf} \times z \times N_f} \right)
\end{aligned} \tag{4}$$

Constraints

$$P_{\mathrm{i}} = \frac{F_{\mathrm{i}} V}{60000} \le P_{\max} \tag{5}$$

$$F_{\mathrm{i}} = \sigma \times A \times Z_{\mathrm{c}} \times C_{\mathrm{mw}} \times C_{\mathrm{w}} \le F_{\max} \tag{6}$$

$$R_{\mathrm{ari}} = 0.0321 \frac{f_{\mathrm{zri}}^2}{r_e} \le R_{\mathrm{ar,max}} \tag{7}$$

$$R_{\mathrm{af}} = 0.0321 \frac{f_{\mathrm{zf}}^2}{r_{\mathrm{e}}} \le R_{\mathrm{af,max}} \tag{8}$$

$$T_{\mathrm{i}} = \left(\frac{C_{\mathrm{v}}}{V} \right)^{\frac{1}{m}} \ge T_{\mathrm{R}} \tag{9}$$

$$V_{\min} \le V_{ri} \le V_{\max} \tag{10}$$

$$V_{\min} \le V_f \le V_{\max} \tag{11}$$

$$f_{\mathrm{z,min}} \le f_{\mathrm{zri},} \le f_{\mathrm{z,max}} \tag{12}$$

$$f_{\mathrm{z,min}} \le f_{\mathrm{zf},} \le f_{\mathrm{z,max}} \tag{13}$$

$$a_{\mathrm{pr,min}} \le a_{\mathrm{pri}} \le a_{\mathrm{pr,max}} \tag{14}$$

Table 2 Face milling operation parameter values

Parameters					
Machine tool: Hurco CNC BMC-20LR Vertical Machining Center					
Cutter tool material: cemented carbide					
Workpart material: medium carbon (150NHB)					
Parameter	Value	Parameter	Value	Parameter	Value
P_{max}	5.6 kW	F_{max}	6000 N	D	25 mm
z	3	B	15 mm	L	240 mm
a_T	8 mm	k_0	0.5 ($/min)	k_t	2.5 ($/cut edge)
ε	5 mm	h_1	0.0007 (min/mm)	h_2	0.3 (min)
t_e	1.5 (min/cut edge)	t_p	0.75 (mm/piece)	r_e	1 mm
$a_{p\ r,\ max}$	4 mm	$a_{p\ r,\ min}$	1 mm	$R_{ar,\ max}$	25 µm
$a_{p\ f,\ max}$	2 mm	$a_{p\ f,\ min}$	1 mm	$R_{af,\ max}$	2.5 µm
V_{max}	300 (m/min)	V_{min}	50 (m/min)	T_R	240 (min)
$f_{z,\ max}$	0.6 (mm/tooth)	$f_{z,\ min}$	0.1 (mm/tooth)	C_w	1.2
C_v	500	m	0.25	C_{mw}	1.3
k_1	5.1175	k_2	478.797	k_3	7.7875
e_1	1	e_2	1	e_3	1

$$a_{pf,min} \leq a_{pf} \leq a_{pf,max} \tag{15}$$

$$a_T = a_{pf} + \sum_{i=1}^{np-1} a_{p_{ri}} \tag{16}$$

$$V_f \geq e_1 V_{ri} \tag{17}$$

$$f_{zri} \geq e_2 f_{zf} \tag{18}$$

$$a_{pri} > e_3 a_{pf} \tag{19}$$

Equation (5) shows that machining power should not exceed the effective power transmitted to the cutting point by the machine tool. Equation (6) is the cutting force constraint [19]. Equations (7) and (8) are the surface roughness constraints for face milling, where r_e is the nose radius of the cutting edge [5]. Equation (9) is the tool life constraint derived based on Taylor's tool life equation. In this study, the period for tool replacement is set at least 240 min. Equations (10)–(15) are the constraints for the decision variables including cutting speeds, feeds, and depth of cuts for both roughing and finishing. Equation (16) limits the cut depth for roughing and finishing not exceeding the total depth of cut demanded. Equations (17)–(19) are the practical relations between the rough and finish cutting parameters. Equation (17) presents that the cutting speed in finishing should be greater than the one in roughing. Equation (18) shows that the feed in roughing should be greater than the one in finishing, while in Eq. (19), depth of single roughing cut is greater than the depth of finishing cut. These three equations are the practical senses any machining operators should have.

3 Proposed evolutionary strategy

The evolutionary strategy (ES) is as one of the three evolutionary algorithms, the other two being genetic algorithm (GA) and evolutionary programming (EP). ES was originally proposed by Rechenberg and Schwefel in the 1960s. The traditional ES consists of several key operators including initialization, selection, recombination, and mutation. Theoretically, the starting population is initialized by an algorithm-dependent method and evolves towards successively better regions of the search space through randomized processes of selection, recombination, and mutation [20]. ES has an advantage over GA and EP in that it uses real values for the decision variables, rather than the binary codes requiring transformation to obtain real values. In addition, recombination (crossover) in GA is emphasized more than mutation, while

Table 3 Best solution found with the proposed ES after 1000 generations

	V (m/min)	f_z (mm/tooth)	a_p (mm)	Cost ($)	SEC (J/mm^3)
Roughing 1st pass	126.870	0.600	3.006	0.283	5.433
Roughing 2nd pass	126.746	0.599	2.999	0.283	5.434
Finishing	126.998	0.279	1.995	0.352	6.138

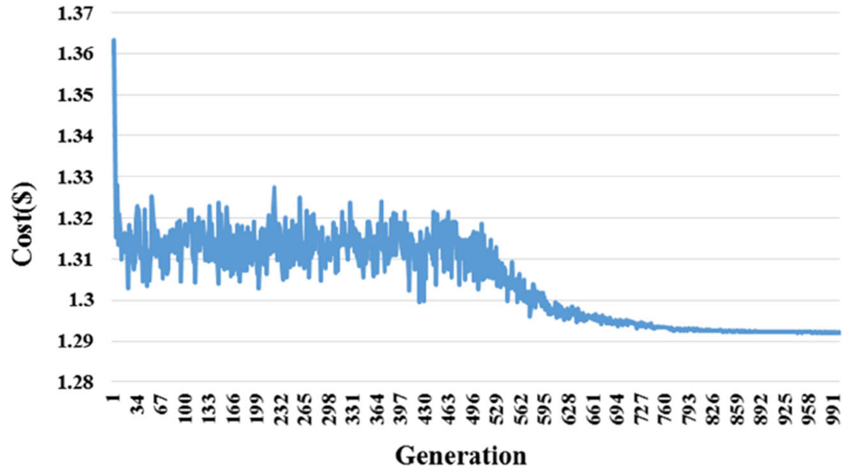

Fig. 2 Trace of search results on unit cost

recombination is not applied at all in EP. In ES, both operators are key elements for successful implementation.

The ES employed in this study was developed based on the version of Wang et al. [21] The first step of the proposed ES determines the initial parent population. Solving this problem involves identifying the optimal values of the nine decision variables (Vr_1, fz_{r1}, ap_{r1}, V_{r2}, fz_{r2}, ap_{r2}, V_f, fz_f, ap_f) resulting in the lowest unit production cost. Each individual parent can be randomly generated as a vector with 18 elements representing the values of the 9 decision variables and their corresponding standard deviation, σ. For example,

$$V_{ri} = V_{min} + U(0,1)(V_{max} - V_{min}) \tag{20}$$

$$\sigma_{ri} = \left| V_{ri} - \left(V_{min} + \frac{V_{max} - V_{min}}{2} \right) \right| \frac{1}{\sqrt{n}} \tag{21}$$

where $U(0,1)$ denotes a random variable of uniform distribution within the interval (0,1). Such an initialization of the standard deviation (Eq. 21) is based on the approach of Franco et al. [22]. This study uses the selection scheme called (μ, λ)-selection in which the μ best individuals out of the set of λ offspring individuals are selected as parents for the next generation. μ best individuals are selected based on the ranking of their UC_T and SEC among the same generation. UC_T and SEC are equally weighted.

There are two commonly used methods for recombination in ES: discrete recombination (sometimes referred to as "dominant recombination") and intermediate recombination. In discrete recombination, the features of individual offspring may remain intact or be mutated from one parent or the other. In intermediate recombination, the features of individual offspring are determined as an average of the two parents' features. The proposed ES uses the intermediate recombination in their global form as proposed by Back and Schwefel [23].

Two selected parents are recombined to form a new individual. This individual has to be mutated to yield an offspring. The

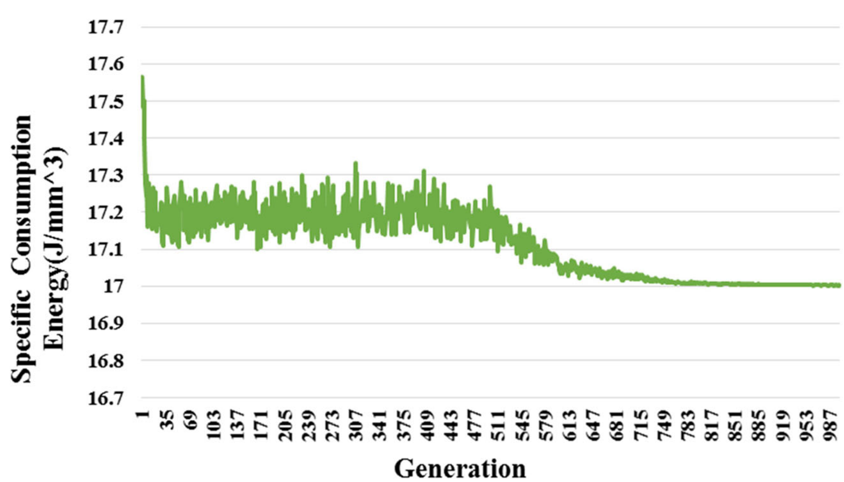

Fig. 3 Trace of search results on SEC

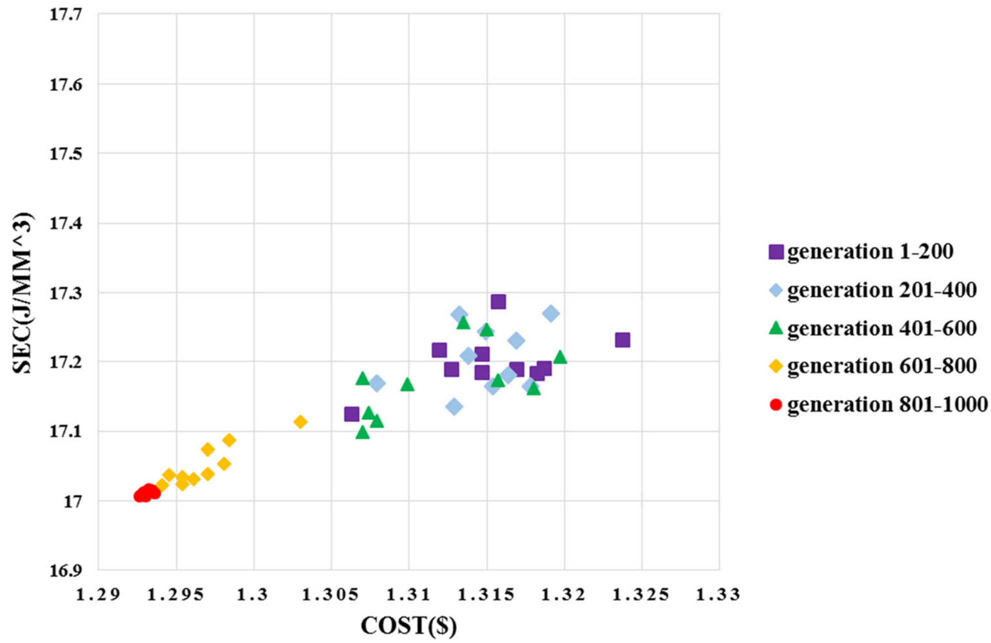

Fig. 4 Best solution search driven by the proposed ES

entire mutation procedure consists of two steps: mutating the standard deviations and then mutating the decision variables.

$$\sigma_r' = \sigma_r \cdot \exp\left(\tau' \cdot N(0,1) + \tau \cdot N_r(0,1)\right) \quad (22)$$

$$V_r' = V_r + N\left(0, \sigma_r'\right) \quad (23)$$

According to Back and Schwefel [23], the values for the parameters τ and τ' in the proposed ES are set as follows:

$$\tau = \left(\sqrt{2\sqrt{n}}\right)^{-1}, \qquad \tau' = \left(\sqrt{2n}\right)^{-1} \quad (24)$$

4 A numerical example

An example is provided to demonstrate the performance of the proposed ES. A face milling operation is performed on the top surface of a rectangular workpart measuring 240 mm long by 15 mm wide. The total cut depth is 8 mm. The machining operation is planned to be completed with two rough cuts and one finish cut. The coefficient values for the SEC model are based on Li et al. [17], with details for the face milling operation presented in Table 2.

After running a thousand of generations of the proposed ES, the best solution obtained has a cost of \$1.292 to produce a single workpart, with total energy consumption for the face milling processes with this machining center of 161.521 kJ. Table 3 provides the best solution found with the proposed ES after running 1000 generations. It can be shown that recommended cutting speed should be set at 127 m/min for either roughing or finishing, the chip load should be set at 0.6 mm/tooth for roughing and at 0.28 mm/tooth for finishing, and the depth of cut should be set at 3 mm for roughing and 2 mm for finishing. Non constraint is violated with the solution obtained. Figures 2 and 3 respectively show the best solutions for 1000 generations in terms of unit cost and SEC. Significantly, diminishing returns are found following 650 generations.

We average the best solutions for every 20 generations with a dot representing each value. Figure 4 plots 50 dots for 1000 generations. The figures show how the progress of solution searching is going. The proposed ES results in a wider solution search for the first 200 generations, after which the dots gradually converge to produce a generally linear relationship. This is because shorter machining time produces lower unit costs, and reducing machining time is dependent on high MRR to minimize SEC.

5 Conclusions

A multi-objective optimization problem for face milling operation is modeled, simultaneously seeking to minimize unit production cost and energy consumption. The proposed model contains practical constraints developed referring to recent literature. An evolutionary strategy-based method is proposed to solve this difficult machining problem. An illustrative example is used to verify its implementation. Results indicate the proposed ES method effectively produces better solutions. MRR is also found to play a key role in optimizing economic and ecological machining performance.

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