Comparative Assessment of Different Optimization Techniques for Turning Operations

تقييم مقارن لطرق التحسين المختلفة لعمليات الخراطة

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ملخص

يقدم هذا البحث دراسة مقارنة لعملية خراطة بهدف تقييم ثلاث تقنيات مختلفة للتحسين، وهي تحكم المنطق الضبابي (FLC)، البرمجة المتتابعة التربيعية (SQP) بالإضافة إلى واحدة من تقنيات التحسين وهى خوارزمية النحل. تم استخدام نموذج رياضي لعمية القطع بالخراطة وتطبيق اثنين من تقنيات المثالية، (SQP) وخوارزمية النحل، مع الاخذ في الاعتبار القيود المختلفة مثل حدود قوة القطع، خشونة السطح، والحرارة المتولدة وعمر الحد القاطع. وقد تم تقييم النتائج ومقارنتها بتلك الناتجة من استخدام (FLC) والمنشورة مسبقا. وقد تبين أنه على الرغم من ان خوارزمية النحل أعطت نتائج مقبولة، ضمنت تقنية (SQP) تحقيق ظروف القطع المثلى. كذلك تم استنتاج ان (SQP) هي أفضل أسلوب تحسين لمعالجة هذه المشكلة، خاصة عند مقارنتها مع أداء الطريقتين الأخرتين اللتين تم بحثها في إطار هذه الدراسة.

Abstract

This paper presents a comparative study that was conducted aiming at evaluating three different optimization techniques; namely, linguistic Fuzzy Logic Control (FLC), Sequential Quadratic Programming (SQP), and the Bees Algorithm. Initially, a well-constructed deterministic model of the turning operation was utilized to feed two optimization techniques, (SQP) and the Bees Algorithm. The results were assessed and compared with those already obtained using (FLC) method that was published in the literature. The study outcomes revealed that, although The Bees Algorithm gave acceptable output, the (SQP) technique identified the optimal cutting conditions. As a result, one can argue that the (SQP) is the best technique to tackle such deterministic optimization problem. This is especially true when compared with the performance of the other two methods examined within this study.

Keyword

Optimization Techniques, Turning Model, Linguistic Fuzzy Logic Control (FLC), Sequential Quadratic Programming (SQP), the Bees Algorithm

1. Introduction

Nowadays, the philosophy of modern manufacturing technologies is to produce products in shorter time, with higher capabilities and at the lowest possible production cost. However, due to the dynamic processes and increase of the machining parameters, optimization of these production operations has become essential [1].

Due to the fact that, turning is one of the most important and widely used

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manufacturing processes in engineering industries, it is urgent to undertake a systematic study to maximize the performance of this technology. The study of turning focuses on the features of the cutting tool, the behavior of the workpiece materials, and machining parameters and their consequent effects on the process efficiency and output quality [1]. Optimization techniques play a significant role to improve the performance of the turning process. In particular, optimization of cutting parameters in machining processes is very important to produce high quality products and reduce the product costs [2, 3].

Several optimization studies to determine the optimal cutting parameters have been reported [3-12]. However, in order to utilize any optimization methodology, initially, reliable mathematical models have to be formulated to associate the cutting parameters with cutting performance. Once the reliable model for turning operations has been constructed, an optimization algorithm is then applied to the model for determining the optimal cutting parameters [4].

It's obvious that optimization of cutting parameters in turning operations is a fruitful field which has attracted researchers to carry out massive optimization trials to improve the process. The literature has shown that most of work carried out was mainly to evaluate the optimum cutting parameters; cutting speed, feed rate, and depth of cut. However, this was conducted without comprehensive considerations of the associated constraints. Especially, the effects of such constraints on the cutting performance such as cutting temperature, cutting forces, power consumption, tool life, and surface roughness has not been fully examined. It is worth emphasizing that detailed cutting model considering inclusive constraints is a complex problem and conducting proper optimization process of such problem is a challenging issue that still needs addressing. Thus, it's important to examine several types of optimization techniques on turning model to predict precisely the resulting effect on cutting performance. In this context, the aim of this research is to assess three different optimization techniques to tackle a general turning model to evaluate the optimum cutting conditions and study their effect on cutting performance.

The remainder of the paper is organized as follows. Firstly, the next section reports on the most related background and provides a specific review of the tuning models and optimization techniques. Secondly, the paper introduces the molding approach utilized to feed the different optimization methods. Thirdly, the following part explains the procedure followed to apply the three different types of optimization techniques on the turning model. Then, the results of the study are discussed paying more attention to carry out comparative analysis of the results of the three optimization methods. Finally, conclusions and perspective are given in the last section.

2. Background

2.1 Turning Model

The pre-stage of applying any optimization strategy is to develop a reliable model that is able to comprehensively capture the effects of the governing parameters. The general analysis of the turning model is based on the popular economic criterion of minimum production time or maximum production rate or minimum cost per components. The constraints to be considered include the machine tool feed and speed limits, maximum power force, spindle torque, power constraints, the obtained surface roughness constraint, and the minimum tool-life limit that may be imposed by the production systems [3-12]. Arrazola et. al. [4] presented the state of art in predictive performance models for machining and scoped on the strengths and weaknesses of the models. The authors classified the modeling techniques into four different types such as analytical, numerical, empirical, and hybrid models. Many researchers worked on machining models to predict the machining performance, Lu et.al. [3], Alberti et.al. [12] used a classical machining economic model for minimizing the production cost, while Chiu et.al. [5] proposed a new multi pass (rough and finish) cutting model for dry turning processes. The proposed mathematical model contains the objective to minimizing the unit of production cost considering the dry effect. Also, a comprehensive set of practical machining constraints especially focusing on dry cutting conditions in several key elements such as the cutting force, cutting power, tool-chip interface temperature, and more importantly the tool life. For maximizing the production rate and minimizing the production cost. Lee et.al. [8] applied the mathematical model on multistage turning operations. Due to the importance of the surface roughness of the machining parts, the researchers try to predict the surface roughness generation by mathematical models. For example, Motorcu [9] developed second order regression model for predicting the surface roughness of AISI 8660 hardened alloy steels. The author concluded that the predicted values were very close to the experimental one for surface roughness.

2.2optimization Techniques

The aim of optimization technique is to provide optimal or near-optimal solution(s) to the overall optimization problem formulated. A large number of techniques has been developed by researchers to solve optimization problems, and may be classified as conventional and non-conventional optimization techniques as shown in **Fig. (1)**. Many researchers applied several optimization techniques on their model to find the optimum solution. For minimization the production cost, Lee et. al. [8] investigated the optimal cutting parameters of multi-stage turning operation for maximizing the production rate. The authors used a sequential quadratic programming method for optimizing the cutting parameters as a state-of-the-art in non-linear programming methods. Abburi et. al. [10] developed a Real Genetic Algorithm (RGA) and Sequential Quadratic Programming (SQP) for minimizing the production time of multi-objective optimization of multi-pass turning process. Munawar et. al. [11] presented an experiment work performed on AISI 1040 carbon steel for optimizing the surface roughness (Ra) by taken into account the effect of machine tool vibration using Taguchi method. The authors showed that a machine tool with low vibration amplitude, large tool nose radius, and low feed rate produced better surface roughness. Saravanan [6] applied Simulated Annealing (SA) and Genetic Algorithm (GA) for obtaining the optimum cutting conditions for minimizing the production cost of a cylindrical stock machined on multi pass (rough and finish) turning process. The authors concluded that (SA) has better results than (GA).

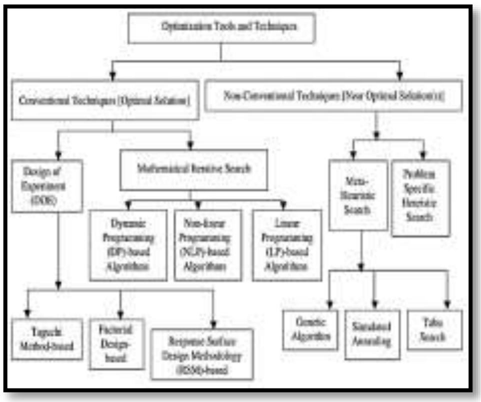

Fig. (1): Classification of optimization techniques in metal cutting process [1]

2.2.1 Lingiustic Fuzzy Logic Control (Flc) Approach

Fuzzy logic control (FLC) approach uses fuzzy sets to represent inputs and outputs and it based on an input/output or block box relationship [13]. Fuzzy logic depends on the expert system knowledge; the approach converts process into a group of linguistic fuzzy set rules. This optimization technique applied to the mentioned turning model for obtains the objective function. Alberti et. al. [12] proposed a new optimization approach which used a fuzzy possibalistic linear formulation for optimizing the cutting parameters in multi pass machining. The authors concluded that fuzzy possibilistic formulation with the genetic algorithm fit very well to machining economics problems and can be obtained in one step. Researchers tried to find the optimal cutting conditions by using (FLC), based on the knowledge and a linguistic fuzzy (if then role); the optimum machining conditions via input cutting constraints for both force and temperature were used to support a decision of machining parameters [13]. On the other hand, the fuzzy output cutting speed values had good correlation with the cutting temperature at different values of depth of cut.

2.2.2 Sequential Quadratic Programming (Sqp)

In this section, the optimum cutting conditions in the turning model can be obtained by using a special optimization tool box in MATLAB, which has wide range of capabilities to tackle different optimization problems such as linear, non-linear, quadratic, least square, and mixed-integer linear [14]. The methodology of the minimization function, ***fmincon***, function is a reliable tool to solve the minimum of a constrained non-linear objective function of several variables starting at user specified initial estimate. ***fmincon*** uses (SQP) method with the active set optimization algorithm and contains a collection of algorithms that govern how a local minimum point is reached. The algorithms are Active-set (AS), (SQP), and Interior-point (IP). Also, ***fmincon*** provides to solve functions linear or nonlinear, constrained or unconstrained problems [15, 16]. Kurdi et. al. [17] introduced a semi-analytical modeling and multi-objective optimization using ***fmincon*** optimization function to find the optimum spindle speed and axial depth of cut of milling process. The authors calculated the trade-off curve of metal removal rate (MRR) and surface location error (SLE). The authors concluded that the maximum (MRR) did not denote any chatter and the measured (SLE) did not show high sensitivity to spindle speed variation.

2.2.3 The Bees Algorithm

The Bees algorithm is a nature inspired algorithm based on the intelligent foraging behavior of honey bee swarm to find the optimum solution. The Bees algorithm describes the foraging behavior, learning, memorizing and information sharing characteristics of honeybees. In the basic of Bees algorithm is combined of random and neighborhood search [18, 19].Many researchers were interested in Bees Algorithm for optimization technique; Yildiz [7] developed an optimization approach for minimizing the cost and find the optimum cutting conditions in multi-pass turning operations based on artificial bee colony algorithm. The Bees Algorithm is intended to mimicry the behavior of honey bees when foraging. Basically, individuals from a bee colony start to search randomly for good patches around the hive. When they came back, they direct other bees to the patch they have found. Each recruiter bee performs a dance, called the waggle dance, which indicates the rich of the source.

3. Modeling Approach

Prior to conducting the comparison between the three optimization techniques, it was urgent to identify well-constructed turning model to feed the optimization techniques for comparative assessment. This section contains the turning model with objective function and related constraints to be used as a bench mark [13].

3.1 Objective Function

The objective function W(x) of turning model used to minimize the production time can be expressed in **Eq. (1)**. In this model W(x) used to minimize the production time (min.) and it's defined as the summation of holding, machining and tool change time. The total production cycle time for one part is composed of three items, i.e., part handling time (t_h) , machining time (t_m), and tool change time (t_c) and tool life (T) can be expressed in **Eq. (1-2):[13]**

$$W(x) = t_h + n_p * t_m + t_c * \frac{n_p * t_m}{T} \quad (1)$$

$$n_p = \frac{\text{The total machining allowance to be removed}(H)}{\text{Depth of cut}(a)} \quad (2)$$

The machining time (t_m) is expressed in **Eq. (3)**, as a function of work piece dimensions length (L) and diameter (D), cutting speed (V) and feed rate (f);

$$t_m = \frac{\pi DL}{1000Vf} \quad (3)$$

3.2 Constraints

The constraints considered [13] include the machine tool feed and speed limits, maximum power force, spindle torque, power constraints, the component surface roughness constraint, and the minimum and maximum tool-life limits that may be imposed by the production systems.The tool life (T) (min.) constraint is taken as the following **Eq. (4)**;

$$T = \frac{C_v^{\frac{1}{m}}}{V^{\frac{1}{m}} f^{\frac{p}{m}} a^{\frac{q}{m}}} \geq T_{opt} - \Delta T \quad (4)$$

where; C_v, m, p, q are constant values,

$$T_{opt} = \frac{tool\ cost\ per\ cutting\ edge\ (C_2)}{machine\ and\ labor\ hr\ per\ cost\ (C_1)} \left(\frac{1-m}{m}\right) * 60$$

and ΔT is uncertainty of tool life. The chip tool interference temperature constraint (θ_c) (ºC) is taken as the following **Eq. (5)**;

$$\theta_c = \beta_0 V^{\beta_1} f^{\beta_2} a^{\beta_3} \leq \theta_U + \Delta\theta \quad (5)$$

where; β_i = (i = 0,1,2,3) are empirical parameters, θ_U is the maximum allowable temperature and $\Delta\theta$ is uncertainty of chip tool interference temperature by which the boundary is moved and

The cutting force (Fc) (Kg) constraint is taken as the following **Eq. (6)**;

$$F_c = \frac{K_1 K_2}{(\sin\chi)^{1-x}}\, a\, f^x V^{x1} \leq F_{cu} + \Delta F_c \quad (6)$$

where; K_1,K_2, x, x_1 are constant values, F_{cu} is the maximum force and ΔF_c is uncertainty of the cutting force by which the boundary is moved.

The power consumption (P_c) (KW) constraint in the turning operation is given by **Eq. (7)**;

$$P_c = \frac{F_c V}{60000\,\eta} \leq P_m + \Delta P \quad (7)$$

where P_m is the input power, ΔP is the uncertainty of cutting power and η is the mechanical efficiency.

The limitation of surface roughness is necessary to insure the quality of machining operation, the empirical equation of the surface roughness (R_z) (µm) constraint is given by the following **Eq. (8)**;

$$R_z = K\, V^{\alpha_1} f^{\alpha_2} a^{\alpha_3} \leq R_p + \Delta R \quad (8)$$

where; K, α_1, α_2 and α_3 are the empirical parameters,$R_p$is the allowable surface roughness and ΔR is the uncertainty of surface roughness. The upper and lower bounds to limit the value of the cutting speed, feed and depth of cut defined as the following **Eqs. (9-11); [13]**

$$V_{min} \leq V \leq V_{max} \quad (9)$$

$$f_{min} \leq f \leq f_{max} \quad (10)$$

$$a_{min} \leq a \leq a_{max} \quad (11)$$

The performance of the three optimization techniques will be assessed; the work conducted with this paper includes applying only (SQP) in addition to the Bees algorithm. The results obtained will be compared with those already reported using (FLC) [13]. As a result, to keep the same modeling conditions, the uncertainty values of the cutting parameters will be taken compared with results of (FLC) [13].

4. Applied Optimization Techniques

4.1 Linguistic Fuzzy Logic Control (Flc) Approach

The optimum cutting conditions considering the uncertainty values of constraints by using (FLC) on the previous turning model [13].

4.2 Sequential Quadratic Programming (Sqp)

The function ***fmincon*** applied on turning model to find the optimum cutting conditions. First of all, it is important to define the objective function as given in the following **Eq. (12)**; [13]

$$W(x) = 1 + \left[\frac{6}{x_3} * \frac{\pi*50*300}{1000*x_1*x_2}\right] + \left[\frac{\left[\frac{6}{x_3} * \frac{\pi*50*300}{1000*x_1*x_2}\right]}{\frac{7^5}{[x_1^5 * x_2^2 * x_3^{0.75}]}}\right] \qquad (12)$$

where; W(x) is the objective function of minimizing the production time, the cutting speed is x_1, feed is x_2 and depth of cut is x_3. Then , the constraints considered include the limits of cutting speed, machine tool feed, depth of cut limits, maximum power force constraint, power consumption constraint, the surface roughness constraint, and the allowable tool-life limits. The procedure followed to undertake the (SQP) algorithm is as shown in **Fig. (2)**.

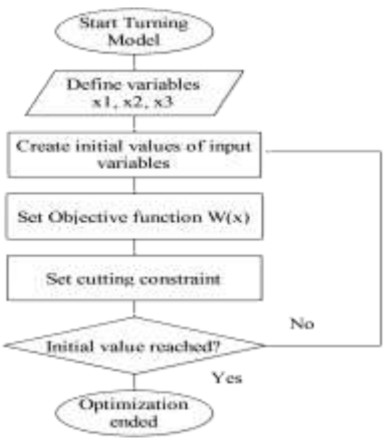

Fig. (2): Basic flow chart of SQP Third, minimizing the production time can be obtained and values of cutting conditions.

4.3 The Bees Algorithm

The optimal cutting condition can be determined using the Bees algorithm to obtain the minimum production time. First of all, the Bees algorithm starts to find the optimum condition by setting an initial random values of x(1), x(2), and x(3) and applied them on the fitness function W(x). After that, the algorithm tries to find the optimum values in neighborhood sits and compare it with the initial one to get which site get an optimum fitness function. Bees Algorithm then tries to evaluate between sites to find the optimum solution, based on the program stopping criteria. The Bees Algorithm then stops its Iterations and the best solution is presents. The following pseudo code shown in **Fig. (3)** for minimizing the production time and find the optimum cutting conditions.

Pseudo code of basic Bees Algorithm

1. Initialize population with random x(1),x(2),and x(3).

2. Evaluate fitness [W(x) $= 1 + \left[\frac{6}{x_3} * \frac{\pi*50*300}{1000*x_1*x_2}\right] + \left[\frac{\left[\frac{6}{x_3} * \frac{\pi*50*300}{1000*x_1*x_2}\right]}{\frac{7^5}{[x_1^5 * x_2^2 * x_3^{0.75}]}}\right]$] of the population.

3.While (stopping criterion not met)

//Forming new population.

4. Select sites of x(1),x(2),x(3)with the best solution W(x) for neighborhood search.

5. Recruit bees for selected sites (more bees for best e sites) and evaluate W(x).

6. Select the fittest bee from each patch.

7. Assign remaining bees to search randomly of x(1),x(2),and x(3) and evaluate their fitness's W(x).

8. End While.

Fig. (3): Pseudo code of minimum production time W(x)

5. Results and Discussions

The results of applying three different types of optimization technique on general turning model, under uncertainty constraints are presented in this section. However, this part of study pays more attention to undertake impartial comparison of the achievable results of cutting variables.

5.1 Comparison Between Optimum Cutting Condition With Optimization Techniques

After applying two different types of optimization techniques and then comparing the results of production time value between (FLC) approach, (SQP) and Bees Algorithm, the results are illustrated in **Table (1)**. This comparison has applied on the same turning model considering the same uncertainty values of constraints. The minimum production time obtained when applying (SQP) and Bees Algorithm were 308 min and 359 min, respectively. However, (FLC) approach gave $1.868*10^5$ min which is unreliable for production time for machining parts.

Table 1: Optimum Cutting Conditions

Cutting Conditions	(FLC)	(SQP)	Bees Algorithm
Objective Function W(x) (min)	**$1.868*10^5$**	**308**	**359**
Cutting Velocity (V) (m/min)	**88**	**18**	**15**
Feed Rate (f) (mm/rev)	**0.29**	**0.05**	**0.06**
Depth of Cut (a) (mm)	**6**	**1.4**	**1.02**

In this context, the minimum value of best production time has optimum cutting condition; cutting speed, feed rate and depth of cut. First, the optimum cutting speed showed that the value of cutting speed has recorded an optimum value of 18 m/min. for (SQP) method. On the other hand, (FLC) approach and the Bees algorithm and gave approximate values of 88 and 15 m/min., respectively. Second, the optimum feed rate has recorded an optimum value of 0.05 mm/rev and 0.06 mm/rev for (SQP) and Bees Algorithm respectively. Also, (FLC) approach has an optimum feed rate at 0.29 mm/rev. Finally, the optimum depth of cut has an optimum value of 1.4 mm for (SQP) method. On the other hand, the value of depth of cut for (FLC) approach has value of 6 mm and Bees algorithm has a value of 1.02 mm.

5.2 Effect of Cutting Conditions On Cutting Performance

This section presents a comparison between the three types of optimization techniques and the cutting performance such as cutting temperature, cutting force, power consumption, tool life, and surface roughness. The following comparison studied the effect of different cutting speed at altered depth of cut for constant feed rate for the three optimization techniques. First of all, the effect of cutting conditions on cutting temperature, as shown in **Fig.(4)**, reveals that (FLC) gradually increased to reach 600°C at speed of 88 m/min. On the other hand, both (SQP) and Bees Algorithm followed almost the same trend of the cutting temperature with values of 280ºC and 260ºC at cutting speed of 18m/min and 15m/min, respectively.

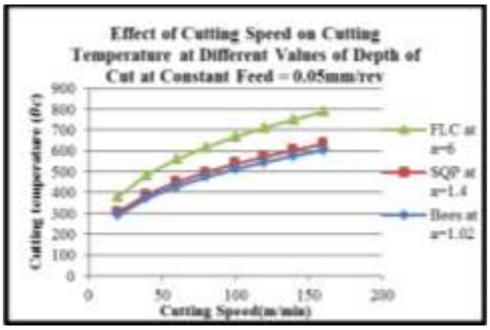

Fig. (4): Effect of identified cutting conditions on Cutting Temperature (θ_c)

Secondly, **Fig. (5)** shows that there is a slight decrease on cutting force between (SQP) and Bees algorithm which resulted values of 100 Kg and 70 Kg at 18 m/min and 15 m/min. respectively. On the other hand, (FLC) gave a high point reach to 240 kg at 88 m/min. Bees algorithm has lower cutting force than other techniques.

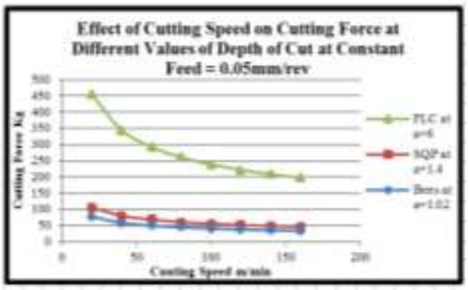

Fig. (5): Effect of identified cutting conditions on Cutting Force (F_c)

Thirdly, the power consumption used to machine the workpiece was 0.4 KW when applying (FLC) at 88m/min. as shown in **Fig. (6)**, on the other hand, it needed only 0.026 KW and 0.024 KW when applying the other two techniques (SQP) and the Bees algorithm at 18 m/min and 15 m/min respectively. The effect of the identified cutting conditions on power consumption of Bees algorithm showed lower power consumption than the other techniques

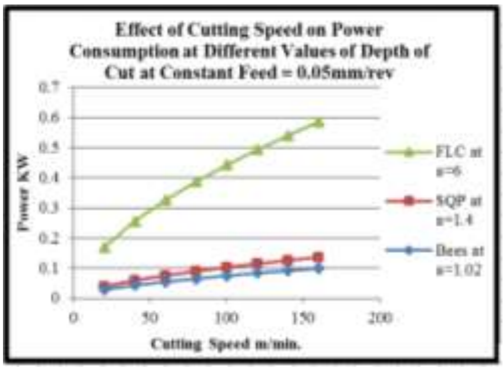

Fig. (6): Effect of identified cutting conditions on Power Consumption (P_c)

Fourthly, surface roughness (R_Z) is one of the significant evaluations of the accuracy for the product. **Fig. (7)** shows that (SQP) and Bees Algorithm identified values associated with rough surface near to 1µm. However, (FLC) has determined the optimum surface with value of 0.8µm.

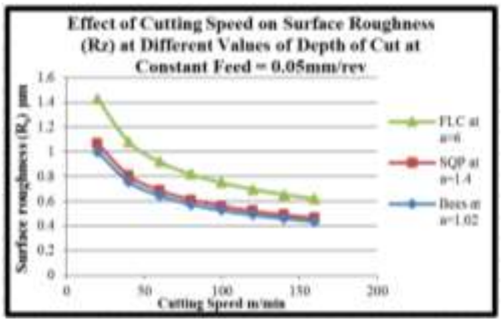

Fig. (7): Effect of identified cutting conditions on surface roughness (R_z)

Finally, **Fig. (8)** shows the effect of optimization techniques on tool life. Obviously, it revealed that (FLC) led to too short tool life of 5.3*10^{-4}min. Conversely, (SQP) and Bees Algorithm resulted values associated with long tool life of 1.63 minute and 2 min, respectively. This is attributed to the effect of low cutting speed which allows the tool to live longer time comparing with (FLC) that determined high cutting speed of 88 m/min.

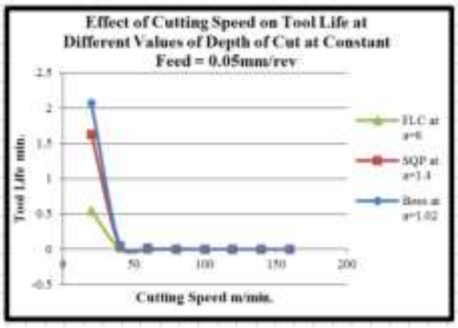

Fig. (8): Effect of identified cutting conditions on Tool Life (T)

6. Conclusion

This paper has reported on a theoretical study undertaken to conduct a comparative assessment between different optimization techniques that were involved conventional and non-conventional techniques, (FLC), (SQP) and the Bees algorithm. Well-constructed turning model for minimizing the production time of unit part was optimized using the three techniques under the same constraints and uncertainty values. The aim was to identify the best minimum production time under uncertainty variables and the effect of optimum cutting conditions on cutting performance such as cutting temperature, cutting force, power consumption, tool life, and surface roughness.

Followings are some specific conclusions drawn based on the results of the carried out analysis.

- The comparison between three types of optimization techniques on turning model for obtaining the minimum production time under uncertainty constraints revealed that sequential quadratic programming (SQP) gave better results of minimum production time and cutting conditions than the other ones. However, the Bees Algorithm, as a powerful genetic algorithm provided very acceptable results. This especially valid in case of stochastic problems to be optimized.
- Fuzzy logic control led to very large production time because of the effect on high cutting speed on tool life, fuzzy logic control (FLC) resulted very high value, out of range, that negatively influence the cutting performance.
- The Bees algorithm has good effect on cutting temperature, cutting force, consumption power and tool life compared with other techniques.
- One can conclude that the difference between optimization techniques depends on the user needs. However, in this problem, (SQP) has needed the minimum time to reach the optimum solution compared with other techniques.

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