

Extreme Learning Machine and Particle Swarm Optimization in optimizing CNC turning operation

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Abstract. The CNC machine is controlled by manipulating cutting parameters that could directly influence the process performance. Many optimization methods has been applied to obtain the optimal cutting parameters for the desired performance function. Nonetheless, the industry still uses the traditional technique to obtain those values. Lack of knowledge on optimization techniques is the main reason for this issue to be prolonged. Therefore, the simple yet easy to implement, Optimal Cutting Parameters Selection System is introduced to help the manufacturer to easily understand and determine the best optimal parameters for their turning operation. This new system consists of two stages which are modelling and optimization. In modelling of input-output and in-process parameters, the hybrid of Extreme Learning Machine and Particle Swarm Optimization is applied. This modelling technique tend to converge faster than other artificial intelligent technique and give accurate result. For the optimization stage, again the Particle Swarm Optimization is used to get the optimal cutting parameters based on the performance function preferred by the manufacturer. Overall, the system can reduce the gap between academic world and the industry by introducing a simple yet easy to implement optimization technique. This novel optimization technique can give accurate result besides being the fastest technique.

1. Introduction

Currently, the metal cutting sector has been expanding as it is widely used for the production of home appliance, automotive industry, building construction, shipbuilding and aerospace industry; these industries are well-equipped with large machine for the use of their employees in metal cutting activities. Out of all the processes, turning operation has been commonly used in the experimental work of metal cutting [1].

There are two types of lathe machine available and still in use: conventional lathe and computer numerical control (CNC) machine. The manufacturers for machine tool produced computer numerical control (CNC) machine for the purpose of maximizing the capability of the conventional lathe that has the capability of reducing cost, producing highly accurate part and increasing the efficiency of the machine tool.



The CNC machine is controlled by manipulating cutting parameters that could directly influence the performance of the process. This concern is also mentioned by Park and Kim in their review that changing the parameters provides better quality as well as accommodating the machinists in the increase of profit and productivity [2].

In the industry, the machinists have to handle the parameters according to their experiences or by the help of the manual handbook that is suggested by the tool supplier. It is possible for people to learn from their experiences and they can also easily learn from a manual handbook. However, the selected cutting parameters are barely at their optimal value. Therefore, many studies have been done by researchers for the introduction of optimization techniques in the effort to solve this problem.

Many optimization techniques such as statistical regression technique and Artificial Intelligence (AI) were applied to obtain the optimal parameters for the desired performance function. Nonetheless, the industry still uses traditional technique to obtain the optimal value. The lack of knowledge on optimization techniques is the main reason for this issue to be prolonged. In this paper, a system has been made to reduce the human intervention in selection of optimal cutting parameters for CNC turning operation. This system need to be fast and effective technique for the machinists to select the right cutting parameters to improve the production.

The paper is organised as follows: Section 1 is the introduction; Section 2 is the literature review of optimization system; Section 3 explains the modelling and optimization technique in determining the cutting parameters; Section 4 describes the proposed graphical user interface; Section 5 discusses the optimization results; and the last section presents the conclusion of this study.

2. Literature Review

There are many computer aided manufacturing(CAM) software available for CNC turning process such as MasterCAM and Vericut. These software offer tool selection, CNC code generation, and process simulation. However, the optimization tool that is available in certain software is limited to minimization of time. Some of the software provide suggestion for the cutting conditions, but these parameters only consider the type of tool and material that are used in the process, for example, MasterCAM. The available software also requires too many variables and it is difficult to be used [3].

There are research done in the effort to develop a system that could optimize the manufacturing process. However, most of the system only focus on the optimal tool for the process. In 2001, Mookherjee has developed a tool selection software called EXTOOL that could help in choosing the right tool and material, as well as inserting geometry based on the requirement by the user [4]. There are also research done in computer aided process planning system in identifying the best cutting tool for the machining operation [5, 6, 7, 8].

The expert computer aided cutting tool selection (EXCATS) was developed to select cutting tools and conditions for major turning operations [9]. Gecevska has introduced optimization of milling and drilling (OPTIMAD) and Genetic Algorithm for machining optimization (GAMO) to optimize and analyse machining conditions in multipass NC machining operation, specifically in milling and drilling operation [10].

One of the major drawbacks of the existing system is that it does not consider numerous parameters of influential factor. According to Kalpakjian, there are many factors that could influence the turning process, including tool (its material, geometry, and shape), work piece (material, condition, and temperature), cutting parameters (speed, feed rate, and depth of cut), the use of cutting fluid, chip formation, the characteristics of the machine tool (feed and speed ranges), work-holding devices, and

part characteristic (geometry, accuracy and finish) [11]. It is important to consider all these factors in order to obtain the optimal parameters. Therefore, the experimental design based optimization is preferred.

Numerous studies have identified that the experimental design based optimization techniques can achieve the desired performances for not only in turning operations [12] but also in many manufacturing operation such as drilling [13, 14], milling [15], injection moulding [16, 17], and electrical discharge machining [18, 19]. According to the literature, the optimal process parameters that were obtained by the researchers through the optimization techniques have proven to provide the desired performance for that particular process.

Nalbant et al. has used Taguchi method, the smaller-the-better characteristic, in optimizing the parameters for surface roughness while Mandal et al. evaluate the influence of cutting parameters using combination of response surface methodology (RSM) and Taguchi as the optimization [20, 21]. Since most of the conventional optimization often stuck at local minima, the researchers move to nonconventional or evolutionary optimization to determine the optimal parameters. Zuperl and Cus in their research using genetic algorithm (GA) to determine the optimal cutting parameters for turning cast steel material [22].

Among the artificial intelligent system, Huang et al. has introduced extreme learning machine (ELM), a new technique which simplify single layer feed forward neural network (SLFN) technique and requires less user-defined parameters which lead to fastest technique [23]. It also has a structure that is similar to neural network, which is equipped with an input layer, a hidden layer, and an output layer as shown in Figure 1.

Since the introduction of ELM, numerous researchers have investigated the technique for regression or classification problem. The results show that the ELM performed better than other modelling technique [24, 25, 26, 27]. ELM is identified as an extraordinarily fast learning algorithm. Unlike the traditional SLFN, the weight in ELM does not need to be tuned and it can perform well even with insufficient data [28]. Figure 2 shows the steps of the algorithm.

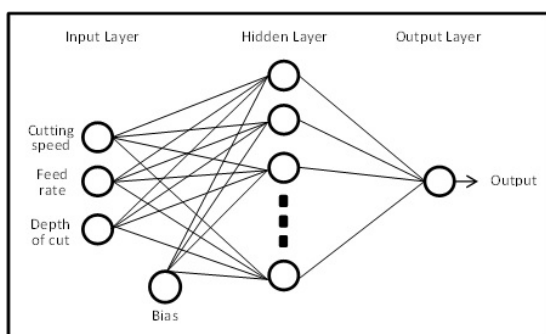


Figure 1. Extreme Learning Machine structure.

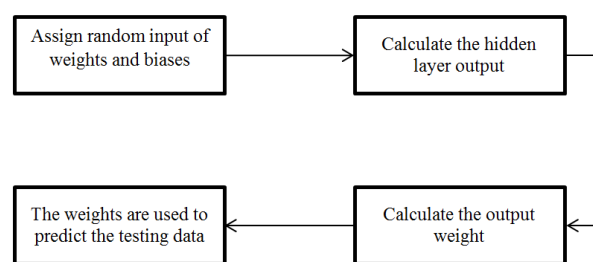


Figure 2. Steps in ELM algorithm.

Since input weight and hidden biases for ELM is assigned randomly, the algorithm is often ends up being unsatisfactory. Xu and Shu has introduced a combination of ELM with PSO to solve the issue [29]. This idea can achieve good generalization performance compared to traditional ELM. The ELM with PSO algorithm can effectively model the process in fast and efficient process [30]. Therefore, the combination of ELM and PSO is used as the modelling technique.

The optimization technique can be applied to obtain the solution for many mathematical problems under the given constraint. From the literature, there have been many articles published on optimization in the effort to prove the efficiency and accuracy of the existing optimization techniques [22, 31, 32, 33]. The Genetic Algorithm is widely used in many applications because it was introduced earlier than the other techniques. However, the comparison of the literature on the optimization technique has discovered that an optimization technique called Particle Swarm Optimization (PSO) has the ability to outperform other techniques [34, 35, 36, 37]. The Particle Swarm Optimization is simulated based on the bird flocking and fish schooling model. According to Chavan and Adgokar and Kim et al., PSO is simple and easy to be implemented [38, 39]. Besides that, Boudjelaba et al. mentioned that PSO is less complex and requires less parameter to adjust as this technique has no mutation and crossover operator compared to GA. Moreover, PSO tends to converge faster than GA [40]. Therefore in this study, PSO is chosen as the optimization tool and the improver to converge ELM.

However, in order to implement this technique in industry, the machinist need to understand throughly the optimization technique. Therefore, a graphic user interface of optimization technique is needed to reduce the human intervention. This intelligent system will require less time to operate, provide accurate results, and easy to understand.

3. Optimization System

There are two stages in the optimization system. First, the modelling of input-output and in-process parameters will produce a mathematical input for the formulation of the process objective function. The second stage is the optimal or near optimal conditions calculation for the turning process. Both stages, as depicted in Figure 3, require either mathematical approaches or artificial intelligent techniques to achieve the goal of optimization.

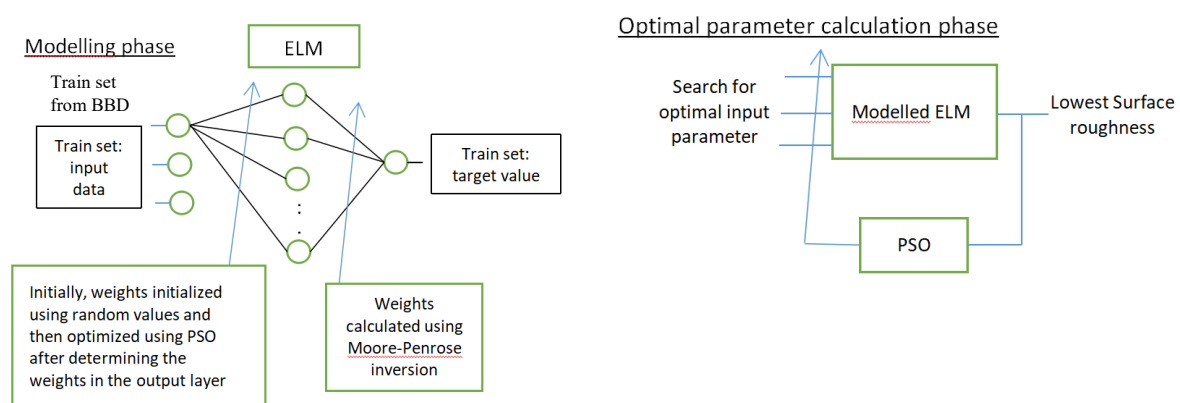


Figure 3. Diagram describing the overall system.

The relationship of input-output and in-process parameters is important to develop the model. This relationship can be determine based on the experimental works done in the manufacturing process. In this study, the Box Behnken Design (BBD) was selected as the design of experiment. BBD is also known as the statistical technique that has the lowest number of experimental run, and it is reliable and efficient in developing a model.

For the three level factors, BBD only requires 15 number of runs including two repetitions. It is the best design for fitting a quadratic model. This is because, the geometry of this design suggests a sphere within the process space. Therefore, the prediction model can be created by using the BBD data, which

is much better than other design of experiment technique. Table 1 shows the experimental investigation that uses BBD.

The experimental investigation approach usually employs the regression analysis to build the modelling function. Even though it is a straight forward approach, the result is unreliable. Therefore, this study employed the experiment technique. The industries require less number of runs as the amount of experimental runs could affect the company's production time and cost.

The BBD data will be key into the extreme learning machine with particle swarm optimization (ELMPSO) algorithm in order to train and develop the accurate model.

Consider N data samples of (x_i, t_i) , where x_i is an element of $R_n \times R_m$. The output function for generalized SLFN with L hidden nodes and activation function $g(x)$ is given in Equation 1.

$$f(x) = \sum_{i=1}^L \beta_i g(w_i x_j + b_i), j = 1, 2, \dots, N \quad (1)$$

Table 1. The experimental design using BBD.

Experiment	Parameter 1	Parameter 2	Parameter 3
1	-1	-1	0
2	1	-1	0
3	-1	1	0
4	1	1	0
5	-1	0	-1
6	1	0	-1
7	-1	0	1
8	1	0	1
9	0	-1	-1
10	0	1	-1
11	0	-1	1
12	0	1	1
13	0	0	0
14	0	0	0
15	0	0	0

β_i is the output weight, w_i is the input weight vector and b_i is the bias of the i -th hidden node.

The activation functions are the sigmoid in the hidden layer and a linear function for the output layer. The β_i is determined using Moore-Penrose inverse that is shown in Equation 2.

$$\hat{\beta} = H^+T \quad (2)$$

where H stands for Moore-Penrose inverse of hidden layer output matrix and T is the target. The w_i and b_i is determined using PSO. The particle, x_i^k in the PSO is refer to the input weight and bias. The movement of each particle depends on the local best position, p_i and also guides the best known position found in the search space by other particle, p_g .

$$v_i^{k+1} = wv_i^k + c_1R_1(p_i - x_i^k) + c_2R_2(p_g - x_i^k) \quad (3)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (4)$$

v_i^k is the velocity of i -th particle at k -th iteration in the swarm while x_i^k is the current position of the particle. c_1 and c_2 are the acceleration coefficients which are 2, R_1 and R_2 are two different random numbers between 0 and 1, p_i is the Pbest and p_g is the Gbest that was achieved by the particle in its neighbourhood. The movement of these particles depend on the fitness value calculated using ELM algorithm. The fitness value for each particle refers to the prediction error of the validation data set. The best particle that has the best quality measurement will be updated in every iteration for 100 iterations using the velocity and particle equation until the best solution for the problem is reached.

In order to determine the optimal cutting parameters, the PSO is used again. In this stage, the random value of cutting parameters acts as a particle, adjusts the velocity vector based on the best position (p_b) as well as the best position of the neighbours (p_g) by referring to the best selected performance function at every iteration. Then, the new position can be obtained. In this optimization technique, the ELM acts as an objective function. The best result is the cutting parameters that can satisfy the objective function.

4. Implementation in Matlab

The graphical user interface (GUI) is applied in the development of the system based on the proposed optimization technique. The development of GUI consists of two phases: GUI design and GUI implementation. In the design phase, the overall interface layout can be set up; while in the implementation phase, the interface can invoke modularly designed Matlab source code.

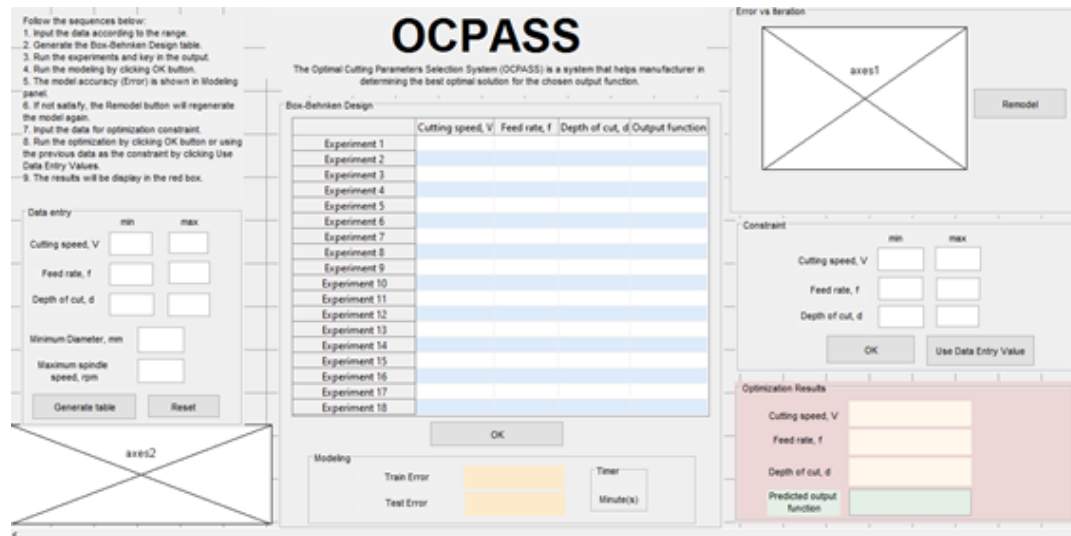


Figure 4. GUI layout in the design area.

The graphical user interface development environment toolbox (GUIDE) that is provided by Matlab is utilized for the development of GUI in an easy and straight forward manner. The main aim of the GUI is to assist the CNC turning operator in selecting the optimal cutting parameters. The GUI components are placed inside the design area using drag and drop technique. Then, the selected component is aligned in its place. Based on the framework, the final interface for the Optimal Cutting Parameters Selection System (OCPASS) is shown in Figure 4.

5. Optimization Result

An experiment is done using AISI 1045 cylindrical bar with 100mm in length and diameter 20mm to validate the system using cutting parameters in Table 2. The objective of the performance that is required by the machinist is that the surface roughness must be lower than $3.2 \mu\text{m}$. In manufacturing industry, the surface roughness value should be $3.2 \mu\text{m}$ and below for jointing and bearing purposes. In order to achieve the objective function of surface roughness, the new cutting edge of CNMG 120404N-GU AC603 is used in each experiment to ensure the accuracy of the reading for the finished surface.

Table 2. The cutting parameters for lower and upper boundary.

Cutting parameters	Lower Boundary	Upper Boundary
Cutting speed (m/min)	80	100
Feed rate (mm/rev)	0.1	0.2
Depth of cut (mm)	0.8	1

Each experiment was carried out until reaching the 40mm cutting length and 17.7mm diameter. The surface roughness tester, Rugosurf 100, is used to record the surface roughness. The samples were measured three times at different locations and the average surface roughness for each sample is recorded. The first step is to input the data entry according to the requirement in Optimal Cutting Parameters Selection System (OCPASS). Then, the machinist is required to generate the BBD table.

The machinist is required to follow the BBD table when running the 18 experiments and recording the surface roughness value in the output function column. Next, the model for the system can be

developed and the OCPASS will display the training and testing error in the graph. During modelling, 15 data will be used as train set while the other three data will be used as test set. The modelling technique is referred as ELM and PSO.

Finally, the optimal cutting parameters are determined after clicking the OK button. The suggested parameters (Figure 5) by the OCPASS are applied in the manufacturing area for AISI 1045. The result for the machining is shown in Table 3. The overall result shows that the difference between prediction and real machining is 24%. This result reveals that the percentage for prediction is quite low although the surface roughness complies with the experimental objective. Moreover, the time taken to complete the work using OCPASS is 36 minutes, which includes the manufacturing process. However, the total time for the system to model and optimize is 6 minutes.

Table 3. The validation experiment's result.

	Cutting speed (m/min)	Feed rate (mm/rev)	Cut depth (mm)	Surface roughness (μm)
OCPASS parameters	86	0.1	0.9	1.91
Real machining	86	0.1	0.9	2.51

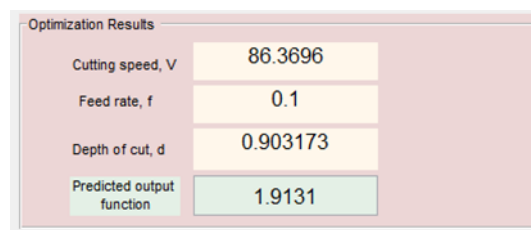


Figure 5. The result of the optimization process using OCPASS.

6. Conclusion

It is proven that optimization technique has been successfully used in several engineering application. However, this technique could not applied in the industry due to time constraint and lack of knowledge. This paper has demonstrated the development of the fastest optimization system together with the graphical user interface for the optimization of cutting parameters in turning operation. This system has three steps, which are design of the experiment using Box Behnken Design, modelling using Extreme Learning Machine with Particle Swarm Optimization, and optimization using Particle Swarm Optimization. This is a novel optimization technique that can accurately optimize besides being the fastest optimization technique. The developed graphical user interface is easy to be understood by all level of users. For future work, this approach can be applied for the optimization of other machining process and extend to multi-objective problems.

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