Proceedings in Manufacturing Systems

Proceedings in Manufacturing Systems, Volume 11, Issue 2, 2016, 57–62 ISSN 2067-9238

END MILLING OPTIMIZATION USING TEACHING-LEARNING BASED OPTIMIZATION ALGORITHM COMBINED WITH CUTTING FORCE MODEL

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Abstract: *In this research, teaching learning based optimization (TLBO) algorithm has been used for determining optimal cutting process parameters in ball-end milling processes where multiple conflicting objectives are present. First, dynamic cutting force components have been modeled using an adaptive neuro-fuzzy inference system (ANFIS) based on design of experiments and then TLBO algorithm is used to determine the objective function maximum (cutting force surface) by consideration of cutting constraints. Ball-end milling experiments have been performed according to the experimental plan. Analysis of the developed approach has been performed to test its validity. The results showed that integrated system of ANFIS and TLBO is an effective approach for solving multi-objective cutting conditions optimization problem in ball-end milling. The high accuracy of results within a wide range of machining parameters indicates that the system can be practically applied in industry.*

Key words: *end-milling, cutting parameters, optimization, TLBO, cutting force, ANFIS.*

1. INTRODUCTION

The proper selection of machining parameters is an important step towards increasing productivity, decreasing costs, and maintaining high product quality. Many researchers have studied the effects of optimal selection of machining parameters of end milling [1]. This problem can be formulated and solved as a multiple objective optimization problem [2]. In practice, efficient selection of milling parameters requires the simultaneous consideration of multiple objectives, including maximum tool-life, desired roughness of the machined surface, target operation productivity, metal removal rate, etc. [1]. In some instances, parameter settings that are optimal for one defined objective function may not be particularly suited for another objective function. Solving multi-objective problems with traditional optimization methods is difficult and the only way is to reduce the set of objectives into a single objective and handle it accordingly.

Therefore population based heuristic algorithms such as evolutionary algorithms (EA) and swarm intelligence (SI) are more convenient and usually utilized in multi-objective optimization problems. These methods are summarized by [3]. Some of the recognized evolutionary algorithms are: Genetic Algorithm (GA) [4], Evolution Strategy (ES), Evolution Programming (EP), Differential Evolution (DE), Bacteria Foraging Optimization (BFO), etc. Some of the well-known swarm intelligence based algorithms are: Particle Swarm Optimization (PSO) [5, 6], Ant Colony Optimization (ACO), Fire Fly (FF) algorithm, etc. All of these algorithms are probabilistic algorithms and require controlling algorithm-specific control parameters [7]. The proper tuning of the algorithm-specific parameters is a very crucial factor which affects the performance of the algorithms [8].

Rao et al. [3] introduced the teaching-learning-based optimization (TLBO) algorithm which does not require algorithm-specific parameters. The TBLO is an efficient alternative over other population-based search algorithms, especially when dealing with multi-objective optimization problems. It is relatively easy to implement and has only two parameters to adjust [3]. The working of TLBO algorithm is explained in the next section.

In our research the adaptive neuro-fuzzy inference system (ANFIS) is used to model the objective function of the process, and TBLO is utilized for solving multi-objective optimization problems observed in milling operations.

2. BASIC OF TEACHING-LEARNING BASED OPTIMIZATION

TLBO is population based method and uses a population of solutions to obtain a global optimum. In TLBO a group of learners (students) is considered as population. TLBO is a teaching-learning process inspired algorithm based on the effect of influence of a teacher on the output of learners in a class. Teacher and learners are the two vital components of the algorithm and describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). Moreover, learners also learn from the interaction among themselves which also helps

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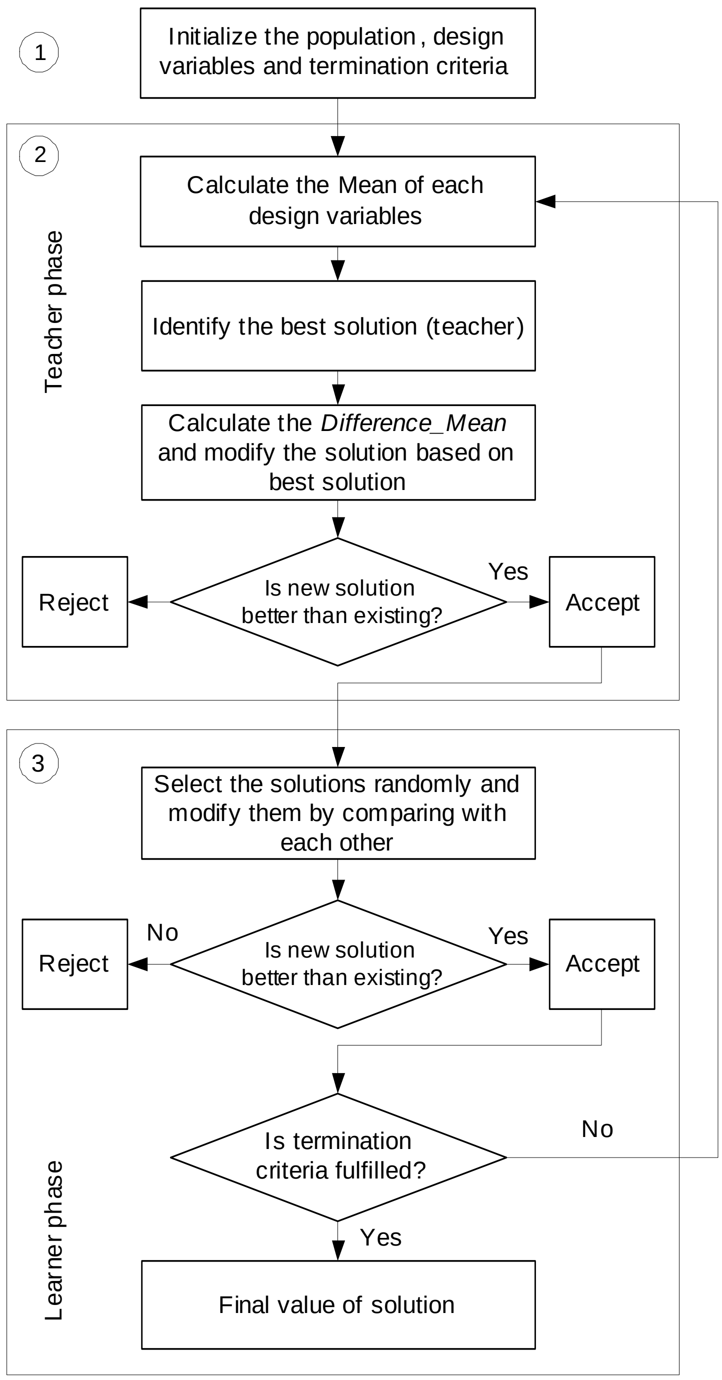

Fig. 1. The flowchart of the TBLO algorithm [3].

in improving their results. The learners' result is analogous to the fitness value of the optimization problem. In the entire population the best solution is considered as the teacher. The output in TLBO algorithm is considered in terms of results or grades of the learners which depend on the quality of teacher.

The working of TLBO is divided into two phases, Teacher phase and Learner phase. Both phases are explained below.

2.1. Teacher phase

In this phase the learners learn through the teacher. A teacher conveys knowledge among the n students (population size, $k = 1, 2, \ldots, n$) and tries to increase the mean result of the class M. At any teaching-learning iteration i, Mj,i is the mean result of the learners in a particular design variable j ($j = 1, 2, \ldots, m$). m is the number of subjects (i.e. design variables) offered to n number of learners. $Xtotal - kbest,i$ is the result of the best student considering all the subjects, who is identified as a teacher for that iteration. The best identified student is considered as the teacher in the algorithm. The students will acquire knowledge according to the quality of teaching delivered and the quality of students in the class.

The difference between the result of the teacher and mean result of the students in each subject is expressed as:

$$Difference\_Mean_{j,i} = r_i \,(X_{j,kbest,i} - T_F M_{j,i}), \qquad (1)$$

where $X_{j,kbest,i}$ is the result of the teacher (i.e. best learner) in subject *j*. T_F is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0, 1]. Value of T_F can be either 1 or 2. The value of T_F is decided randomly using Eq. 2:

$$T_F = \text{round } [1 + \text{rand } (0,1) \{2-1\}]. \quad (2)$$

Based on the *Difference_Meanj,k,i*, the existing solution is updated in the teacher phase according to the following expression.

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,I}, \quad (3)$$

where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$. $X'_{j,k,i}$ is accepted if it gives better function value. All the accepted function values at the end of the teacher phase are maintained and these values become the input to the learner phase.

2.2. Learner phase

In this phase the learners increase their knowledge with the help of mutual interactions. The students can gain knowledge by discussing and interacting with the other students. The learning phenomenon of this phase is expressed below.

Every student has to interact with any other student. Randomly two learners *P* and *Q* are selected such that $X'_{total-\mathrm{P,i}} \neq X'_{total-Q,i}$. $X'_{total-P,i}$ and $X'_{total-Q,i}$ are the updated values at the end of teacher phase.

$$X''_{j,P,i} = X'_{j,P,i} + r_i\,(X'_{j,P,i} - X'_{j,Q,i}),\ \text{if } X'_{total-P,i} > X'_{total-Q,i}, \quad (4)$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i\,(X'_{j,Q,i} - X'_{j,P,i}),\ \text{if } X'_{total-Q,i} > X'_{total-P,i}. \quad (5)$$

Above equations are for maximization problem, reverse is for minimization problem. $X''_{j,P,i}$ is accepted if it gives a better function value

Figure 1 show the flowchart of the TLBO algorithm [3].

3. ANFIS BASED CUTTING FORCE PREDICTION MODEL

In this section an accurate and reliable model for predicting cutting forces during end milling process is outlined. The cutting force prediction model is built according to the ANFIS method. The ANFIS method seeks to provide a linguistic model for the prediction of cutting forces from the knowledge embedded in the trained neural network.

By given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using a backpropagation algorithm. This allows fuzzy systems to learn from the data they are modeling.

FIS Structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs.

Four steps are required to develop an ANFIS system.

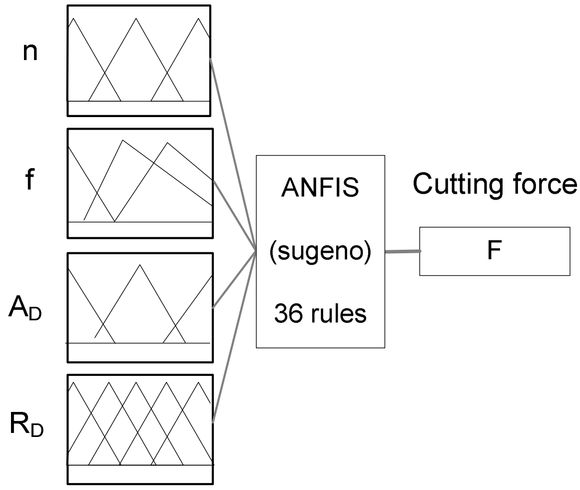

Fig. 2. Architecture of ANFIS cutting force model.

In step 1, the training and testing data are loaded to the system.

The process variables are force sensor readings (*F*), spindle speed (*n*), feed rate (*f*) and depth of cut (A_D / R_D). All the data were scaled. The whole data set is divided into the training and the testing set. Five hundred data points were used in this study. The training data set is used to find the initial premise parameters for the membership functions by equally spacing each of the membership functions.

A threshold value for the error between the actual and desired output is determined.

The FIS architecture and training parameters were defined in step 2.

The optimization method, the tolerance error, the maximal number of epoch, the number of membership functions and the membership functions types are defined.

The fuzzy inference system under consideration has 4 inputs and one output. The inputs are the cutting conditions. The output is cutting force sensor signal.

In step 3, the training phase is accomplished. With the input-output data, the neuro-fuzzy algorithm is trained, and the unknown parameters are identified.

Figur 2 shows the inputs, membership functions, and the fuzzy inference system for cutting force prediction.

During the training stage, the ANFIS adjusts its internal structure to give correct output results according to the input features. The process is terminated when the error becomes less than the threshold value.

During training in ANFIS, 50 sets of experimental data are used to conduct 500 cycles of learning.

Finally, in the fourth step the trained ANFIS is used to predict cutting forces.

4. ADAPTATION OF TBLO APPROACH TO MILLING OPTIMIZATION

In order to find optimal cutting parameters, ANFIS model of cutting forces was integrated with TBLO algorithm. The optimization strategy is shown in Fig. 3.

ANFIS model is developed, and its output is fed into the TBLO algorithm where constraints are defined.

Table 1

Constraints and their expressions

Constraints	Expression	Variables
Feedrate	$f_{\min} \le \frac{1000 \cdot z}{\pi \cdot D} v_c \cdot f_z \le f_{\max}$	z –number of teeth, f_z–feeding per tooth, D –diameter of cutter
Spindle speed	$n_{\min} \le \frac{1000}{\pi \cdot D} v_c \le n_{\max}$	v_c –cutting speed
Radial depth of cut	$R_D \le ae_{\max}$	ae_{max} –max. radial depth of cutting
Axial depth of cut	$A_D \le ap_{\max}$	ap_{max} –max. axial depth of cutting
Power of cutting	$\frac{MRR \cdot Kc}{60} \le P_{dov}$	MRR –metal removal rate, Kc –specific cutting force
Cutting force	$F(f,n) \le F_{ref}$	F_{ref} –desired cutting force
Surface roughness	$R_a \le R_{a\ ref}$	$R_{a\ ref}$ - desired surface roughness

TBLO algorithm is initiated with randomly generated answers in predefined population of students. The student`s answers are optimum solution candidates. ANFIS model predicts cutting forces for each of the student.

Predicted maximal forces are used as an objective function which PSO tries to maximize.

The objective function serves as the only link between the optimization problem and TBLO algorithm.

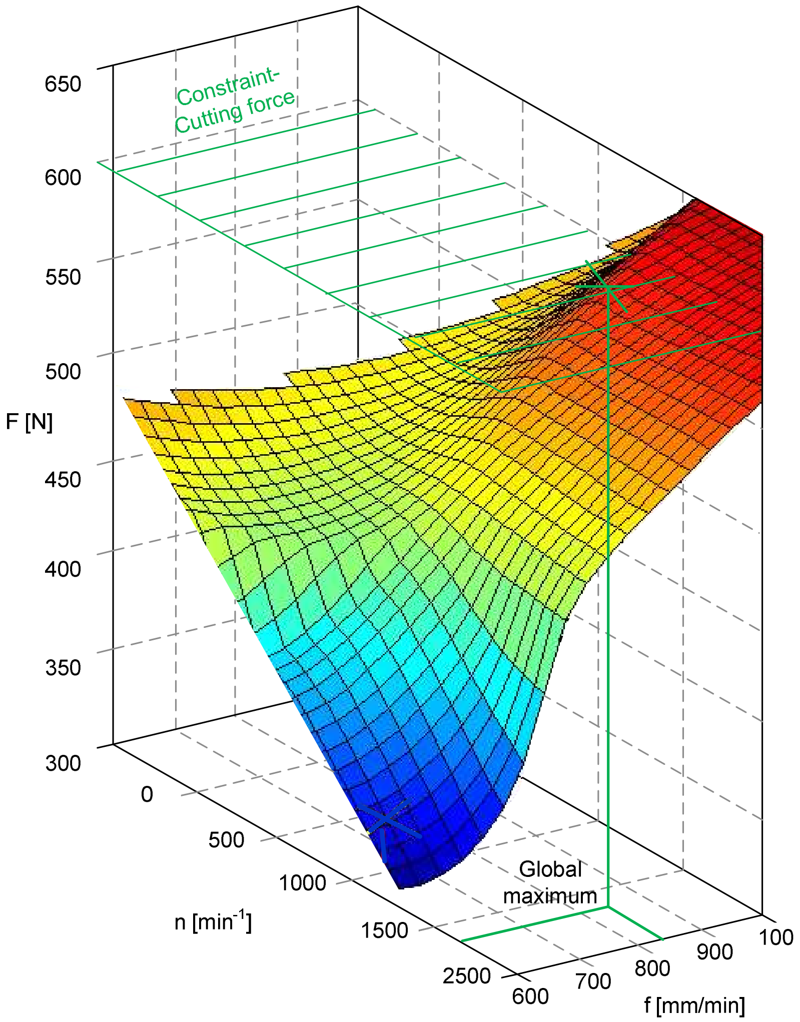

Fig. 3. Results of application of optimal cutting conditions searching procedure.

The optimization process executes in two phases. In first phase, the ANFIS model on the basis of recommended cutting conditions generates 3D surface of cutting forces, which represent the feasible solution space for the TBLO algorithm.

The cutting force surface is limited with planes which represent the constraints of cutting process. Seven constraints, which arise from technological specifications, can be considered during the optimization process. Those constraints are listed in Table 1.

TBLO algorithm generates a population of students-learners during the second phase.

The learners learn through the teacher and at the end phase increase their knowledge by interaction among themselves to find the maximal cutting force.

The best answer of a student which has found the maximal but still allowable cutting force represents the optimal cutting conditions.

The optimization process is depicted by the following steps:

1. Define the optimization problem (maximization of cutting force surface) and initialize the optimization parameters: Population size (k = 8 students), number of generations (i = 20), number of design variables (j = 2 for f and n) and limits of design variables (f_{min}, f_{max}, $n_{min,}$ n_{max}).
2. Generate a random population according to the population size and number of design variables (j = 2).
3. Teacher phase; Calculate the mean of each design variable (f, n), evaluate of objective (cutting force surface) function for each student, identify the best solution (teacher), modify solution based on best solution.
4. Student phase; increase the knowledge of students with the help of their mutual interactions.
5. Termination criteria; steps 3 and 4 are repeated until the generation number reaches a maximum generation number.

Figure 3 shows simplified principle of optimization of cutting parameters by the use of TBLO. In this case, the group of students search for optimal feeding and spindle speed. Optimal feed rate is located at the cross-section of the following two planes: cutting force surface and the limit cutting force plane. The student's answer which is the nearest to mentioned cross-section represent the optimal feed rateand spindle speed.

A group of Matlab m-files forms TLBO software for optimization. This software can be used for optimization of arbitrary non-linear system. The required input parameters required for executing TBLO algorithm are inserted in a software window.

The result of optimization (optimal cutting parameters) is presented to user in a tabular form.

The progress of optimization process can be monitored on graph.

5. TBLO OPTIMIZATION OF CUTTING PARAMETERS-TEST CASE

The repeatability of the TBLO optimization strategy is outlined with presented test case. The accuracy and repeatability of the proposed optimization strategy is first analyzed by simulations, and then it is verified by experiments on a CNC machine tool HELLER BEA02 for 16MnCrSi5 XM steel workpieces [2]. The solid ball-end milling cutter with two cutting edges, of 16 mm diameter and 8° helix angle was selected for experiments.

Table 2

Repeatability of results

Test/Run	n [min^{-1}]	f [mm/min]	F [N]	Nr. of generations
1	1999	828.3	597	15
2	1994	830.5	600	17
3	1998	831.2	601	19
4	1997	839.6	597	23
5	2000	839.1	598	11
6	1999	839.3	599	20
7	2000	828	596	18
8	1996	828.9	597	12
9	1996	828.7	599	23
10	1999	828.4	596	21

The following cutting parameters and constraints were used: milling width R_D = 2 mm, milling depth A_D = 3 mm, $500 \leq n \leq 2500$ min^{-1}, $10 \leq f \leq 950$ mm/min, $F(f, n) \leq Fref$ = 600 N.

The objective function is generated by ANFIS cutting force model.

The goal of this case is to maximize the objective function under given constraints. In TBLO, a population of 10 learners was used and learned continuously until global maximum is found within specified constraints.

The results are outlined in Table 2. Each run corresponds to each time the program is run to find the optimum machining parameters. Table 2 shows optimal cutting conditions along with the number of generations it took to reach that optimum.

This optimization strategy has higher convergence, unlike traditional methods and is always successful in finding the global optimum. The machining time is reduced by 27% as a result of optimizing the feed and speed.

Figure 4 shows a typical student answers pattern toward the optimum solution. Generation 0 represents the random initialization of the student's answers coordinates in the solution space. In subsequent generations, the student`s answers are tracked with "x".

The best student in population is presented with "O". The solution space is marked by the rectangle. An acceptable solution has to be found within this two-dimensional space.

The third constraint on force is also active and as such is not part of these illustrations.

By simulations the efficiency of the optimization approach is demonstrated.

6. CONCLUSIONS

This study has presented multi-objective optimization of milling process by using ANFIS modelling and TBLO optimization algorithm.

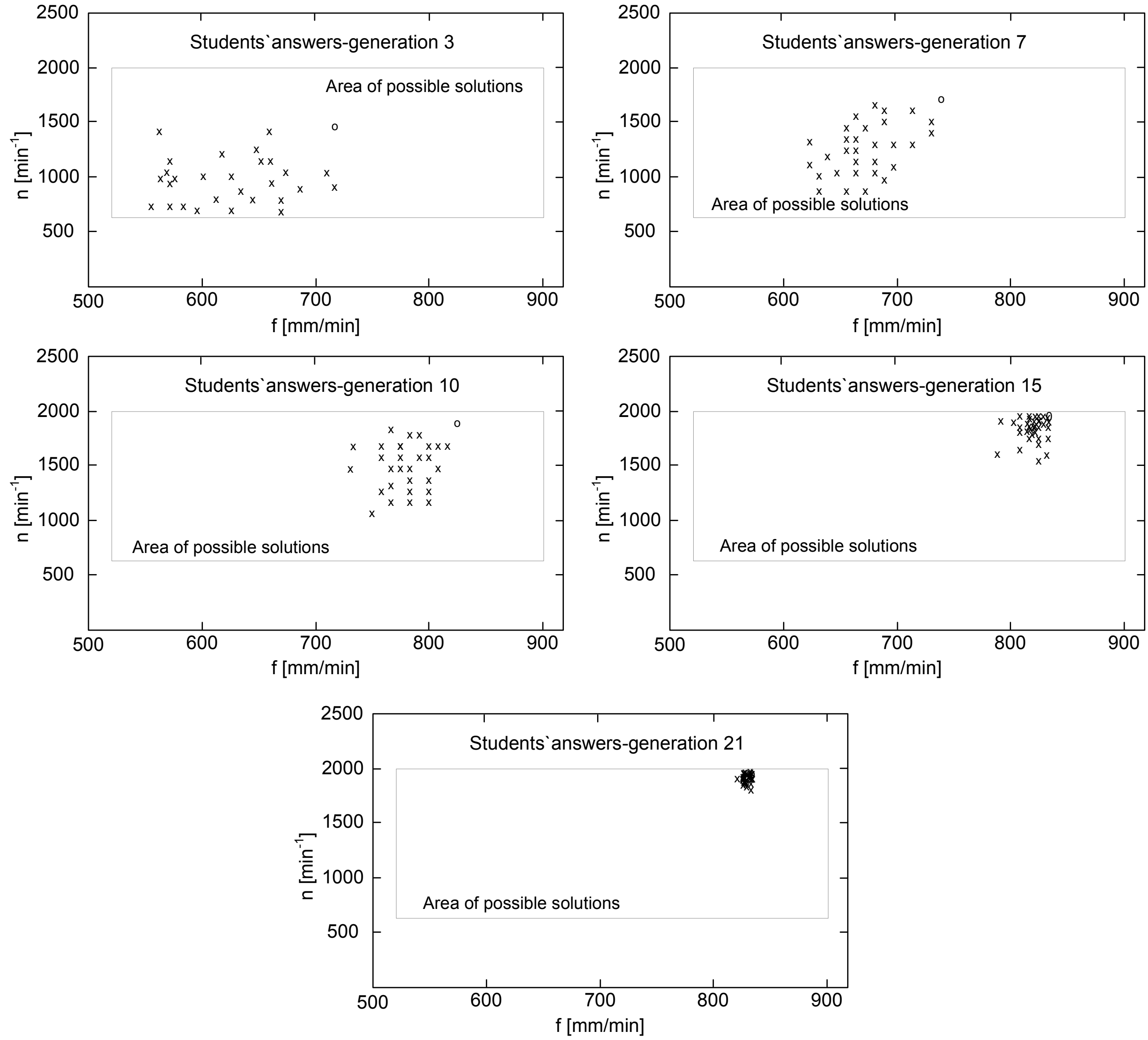

Fig. 4. TBLO simulation,

The ANFIS model was used to predict objective function and TLBO algorithm was used to obtain optimum spindle speed and feed rate for a typical case of milling found in industry. A set of 5 constraints were used during optimization. The experimental results show that the MRR is improved by 19%. Machining time reductions of up to 15% are observed. This paper presents mathematical fundamentals of TBLO optimization.

The optimal cutting conditions obtained by TLBO have been verified through experiments. They have been conducted with optimal cutting parameters to verify the optimization results and effectiveness of the optimization approach. It was found out that the experimental values at optimized cutting parameters are very close to the results obtained by TBLO.

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