El Hossainy *et al.*
Journal of Engineering and Applied Science (2023) 70:7
https://doi.org/10.1186/s44147-023-00174-z

Journal of Engineering and Applied Science

REVIEWS **Open Access**

Machining process parameters optimization using soft computing technique

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Abstract

This work introduces an approach for optimization machinability measures of power consumption, machining time, and the surface roughness (PMS). This approach is starting with market customer's demands, passing by optimizing the machinability measures (PMS), and ending by the optimized cutting conditions. The fuzzy logic was used to define the weights of each of required machinability measurement using method through expert rules depending on factory requirements. Genetic algorithm was formulated for giving optimum output values based on the customer's demands. A neural network was designed for controlling the input cutting conditions with the PMS output parameters. The proposed soft computing technique creates reasonable results compared to experimental results and gives rich investigations for optimizing the output parameters not only for increasing productivity and quality demands but also for saving power consumed. The variation of consumed power, machining time, and surface roughness was calculated based on different customer demand levels. When the machining time and power consumed importance increased, the proposed technique reduced them by about 20% and 10% for the testes case.

Keywords: Machining, Machining power, Machining time, Surface roughness, Surface quality, Optimization, Fuzzy logic, Neural network, Genetic algorithm

Introduction

Selection of the optimum cutting conditions improves the productivity and high quality with minimum cost greatly [1, 2]. Mainly, optimization of the machinability measurements and selection of the optimum cutting conditions are nonlinear problems. So, the researchers used many modeling and optimization methods such as statistical analysis, fuzzy logic (FL), neural networks (NN), and evolutionary computation (EC) which are called as soft computing. Soft computing methods can be defined as improving methodologies for achieving the tolerance of imprecision, uncertainty, and partial truth to achieve robustness, tractability, and low cost [3, 4]. The relation between the cutting conditions and the machinability measures as cutting power, machining time, and surface roughness (PMS) is complex because the trends of these measurements are not uniform.

Mainly, the researchers use one or two soft computing method, where some studies applied one of genetic algorithms [5], neural networks [6], or fuzzy techniques

[7–9], while other studies used combined techniques [10–13]. Without an exception, single or two soft computing techniques could be used. The artificial neural network modeling was used to model the machinability measures such as cutting forces, material removal rate, and surface roughness [14]. Ozel and Karpat utilized neural network modeling to predict surface roughness and tool flank wear over the machining time for variety of cutting conditions. The data sets from measured parameters were employed to train the neural network models. A comparison of neural network models with regression models show that predictive neural network models generally offered the ability to model more complex nonlinearities and interactions than linear and exponential regression models [15]. Cus and Zuperl found that artificial neural networks were suitable for fast determination of optimum cutting parameters during machining, where there was not enough time for deep analysis [1]. X. Ajay et al. developed a neural network model for the surface roughness during turning SS410 steel. They concluded that the neural network can be used to predict the surface roughness with high accuracy compared to regression models [16].

Fuzzy logic was used in machining process for selection of proper cutting conditions, monitoring and prediction of these conditions effect on the process variables, and finally optimization. Mainly, machining processes are nonlinear problems, so developing deterministic model based on the mathematical representation for them is very difficult, and hence, using probabilistic methods is very popular in metal cutting [17–19]. Li et al. used an adaptive neuro-fuzzy inference system (ANFIS) and mentioned that this approach reduces the modeling uncertainty and measurement cost. They concluded that the practical experiment confirmed that their suggested approach had ease of implementation and was reliable [7]. Jegaraj and Babu used soft computing approach employing adaptive neuro-fuzzy approach to predict the process parameters for achieving the desired performance. They concluded that the proposed methodology helped in obtaining desired cutting performance [20]. B. Das et al. applied gray fuzzy logic for minimization surface roughness and cutting forces for Al-4.5% Cu-TiC composite milling [21]. S. R. Chowdhury et al. carried out optimization for aluminum 6082-T6 alloy turning using fuzzy logic integrated with different decision-making methods. All used decision-making methods give the same optimum cutting conditions [22].

Amiolemhen and Ibhadode propose an optimization technique based on genetic algorithms for the determination of the cutting parameters and mentioned that experimental results show that the proposed technique was both effective and efficient [5]. Zain et al. found that the integrated simulated annealing (SA) and genetic algorithm (GA) soft computing techniques had effective approaches for estimating the minimum surface roughness values compared to the experimental data [23].

Roy et al. designed genetic-fuzzy expert system for predicting surface finish in turning using two soft computing tools, namely fuzzy logic and genetic algorithm. He indicated that the proposed system produced an efficient knowledge base of fuzzy expert system for predicting the surface finish in diamond turning. They proposed a genetic algorithm concept to optimize the weighting factors of the network and found that the error when the network is optimized by genetic algorithm reduced to less than 2% [24]. S. Sivarajan et al. used fuzzy logic to predict the surface roughness during turning of EN31 steel.

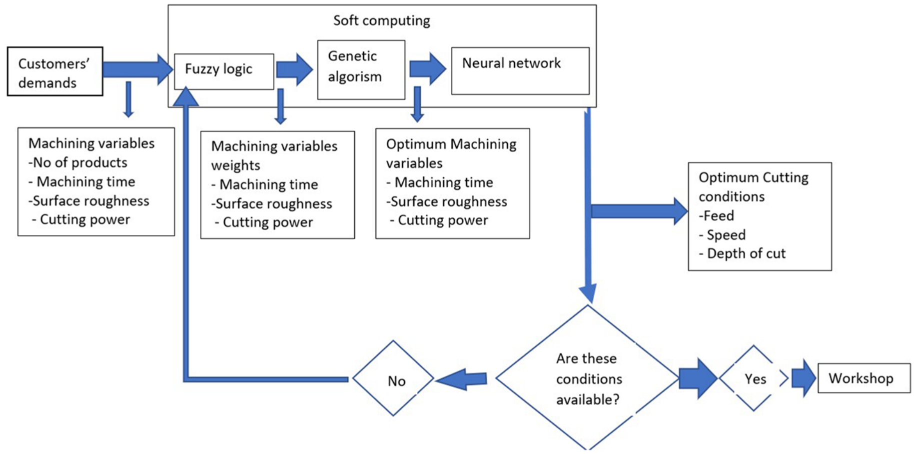


Fig. 1 Flow chart for the porposed technique

Their suggested model was very close to the experimental results with error less than 5% [9].

Generally, machinability measures of PMS cannot be improved in the same cutting conditions, but it depends on the customer requirements. For example, in roughing process, the customer prefers reduction of the machining time and cutting power. While in finishing process, the surface and dimensional qualities become the first priority. This study introduces a proposal for optimization based on what the customer need. This proposal used the fuzzy logic, then genetic algorithms, and then neural network for weighting the PMS based on the customers' needs and then defining the optimum cutting conditions for these needs.

Methods and experimental work

Problem statement

Generally, the machinability of a material is evaluated using the following: cutting power, tool life, chip mechanism, workpiece finish, etc. [25]. Selection of optimum cutting conditions changes the cutting mechanics which in turn is the overall process variables with emphasis on the machining power consumed, the machining time, and the surface quality of the machined surface.

Proposed technique

In this work, integrated approach was developed starting from market customer's demands, passing by optimizing the machining process parameters (PMS), and finally extracting the optimized cutting conditions. Comprehensive approach used objective optimization procedures which were adopted and controlled by using fuzzy logic, neural network, and genetic algorithm handled by controlling different MATLAB Toolboxes. New in this research is that the customer's demands are predominant based on an expert committee, and that the designed fuzzy rules are flexible and can be adapted to fulfill any factory depending on its requirements.

Figure 1 shows a flow chart for the proposed technique. It starts by collecting the customer demands in terms of mass production (number of products), permitted time to finish the work (machining time), product quality (surface roughness), and the cutting power. These demands are fed to soft computing which starts by weighting these demands using fuzzy logic. The genetic algorism takes the demand weights to get out from fuzzy logic to find the optimum PMS based on the customer demands. Finally, neural network computes the optimum cutting conditions. Some experiments were carried out to test and train the neural network.

Fuzzy logic

Fuzzy logic basically was introduced in 1965 for handling problems and has no sharp definition and cannot be modelled mathematically based on its physics [24, 25]. Fuzzy logic was used as a mapper module for predicting accurately the weight of PMS output parameters. This was achieved by delivering the consumer demands (number of products "Qp," delivery date "Td," power factor "Ef," quality of product "Q"). As customer's commands are composed of linguistic terms, fuzzy-expert rules are used to eliminate the complexity of the situation approach and will reduce the modeling uncertainty. Table 1 shows the linguistic rating for each customer demand.

Fuzzy logic converts these PMS input parameters into three output-weighing factors (Ti, U, Ra) presented in Fig. 2. Where the weight of machining time is "a1," the weight of power consumed is "a2," and the weight of surface roughness is "a3" with the membership function using linguistic ratings (low, medium, and high).

The fuzzy rules were designed and fed to adapt the relation between the input PMS and output parameter weights. In this system, a compact selection method is based on expert rules, which were obtained from experimental results and extracted by expert committee. The fuzzy rules were designed to fulfill some requirements; in the factory strategy, all demands were within the range of cutting conditions used in the experimental work in addition to the assigned output parameters PMS.

Table 1 presents the weight results from the expert committee. These weights are flexible and can be adapted to fulfill any factory depending on its requirements. From Table 1, it is clear that the committee decisions were based on some logic expert rules. As an example,

Table 1 Data results from the expert committee

Customer demands	Linguistic rating	"a1" weight of machining time	"a2" weight of power consumed	"a3" weight of surface roughness
Number of products "Qp"	Few	0.40	0.20	0.15
	Med	0.70	0.40	0.10
	Many	1.00	0.60	0.05
Delivery date "Td"	Long	0.40	0.10	0.15
	Med	0.70	0.20	0.10
	Quick	1.00	0.30	0.05
Power factor "Ef"	Cheap	0.20	0.40	0.15
	Med	0.40	0.70	0.10
	Costly	0.60	1.00	0.05
Quality of product "Q"	Excellent	0.05	0.05	1.00
	Good	0.10	0.10	0.70
	Rough	0.15	0.15	0.40

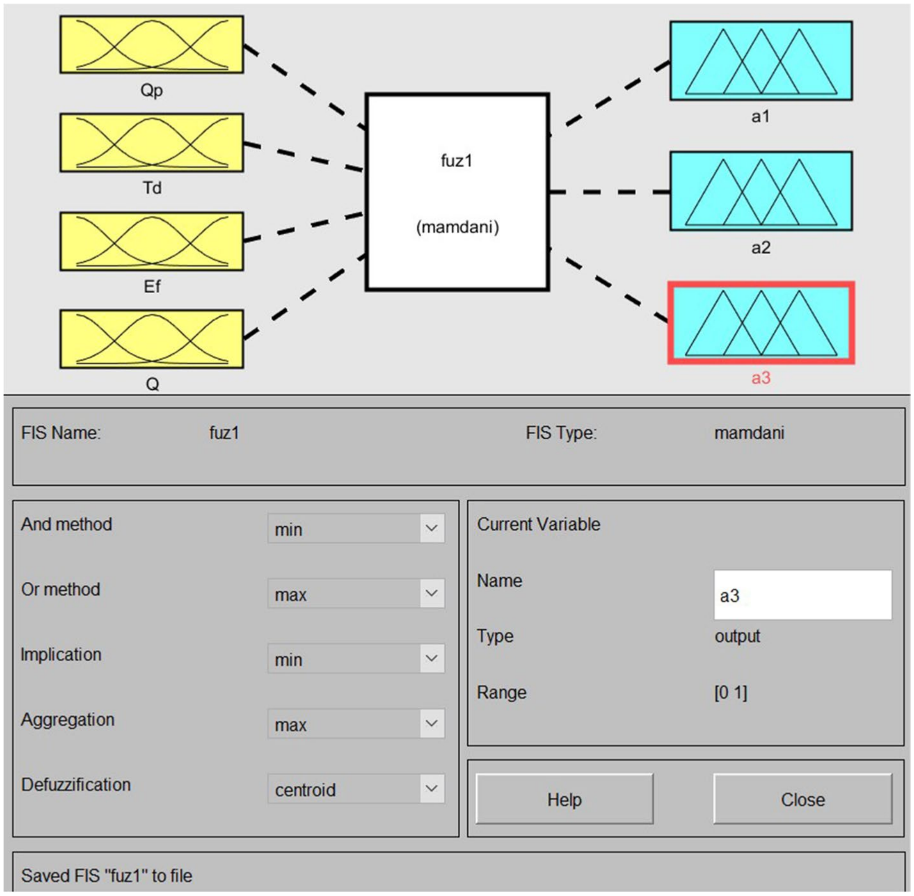


Fig. 2 Fuzzy logic converts PMS input parameters into three output-weighing factors

when the number of products goes from few to many, not only the weight of machining time increases from 0.4 to 1 but also some compensation was done to the weight of power consumed which was from 0.2 to 0.6. This is because when increasing the weight of machining time, machining time will decrease and as a result increasing the rotational speed and increasing the cutting velocity and consequently the power consumed. That is why increasing the weight of power consumed is reasonable for compensation. Also, all weights must practically have a value. The used fuzzy rules were calculated based on the expert committee results by adding the weights and then normalize them between 0 and 1.

This system can be adapted to optimize machining time, machining cost, or profit combined with tool life problem. Different test problems will be presented in the "Experimental work" section for different customer's demands; the optimized cutting conditions and the resulting PMS depending on the factory strategy will be discussed. Once the fuzzy rules are designed properly suiting the factory strategy, the output optimization results will be more efficient.

Neural network modeling

Neural network was used as a measurement module that provides better prediction capabilities because they generally offer the ability to model more complex nonlinearities and interactions than linear and exponential models can offer [15]. Marquardt-Levenberg backpropagation algorithm was used in this work for reaching the best training performance. The network training function "trainlm" updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm is often the fastest backpropagation algorithm in the toolbox and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms [26]. Hidden layer functions are hyperbolic tangent sigmoid transfer, while the output layer function is the pure line.

The neural network input data was based on a real experimental work presented in the "Experimental work" section. The experimental data of the measured PMS output parameters were utilized to train the neural network module (after being normalized and shuffled) using about two-third of the experimental data and checked by the rest of data. Trained neural network module was used in predicting PMS output parameters for different cutting conditions.

Genetic algorithm

Genetic algorithms are popular technique in optimization machining process for both traditional and nontraditional [27, 28]. Genetic algorithm was used as an optimizer for minimizing the cost function (c) shown in Eq. 1. This function was designed to include all PMS with their weights in a simple way. It is depending on the weights of PMS determined from the fuzzy mapper module and the trained neural network module for predicting optimum PMS output parameters for different cutting conditions. It is flexible for each firm to design the cost function depending on its own strategy. The fuzzy logic, neural network, and genetic algorithm modules were managed and controlled by MATLAB Fuzzy Logic Toolbox.

$$C = a1 * (Ti) + a2 * (U) + a3 * (Ra) \tag{1}$$

Experimental work

Turning experiments in dry medium were conducted on a center lathe for machining mild steel (St. 37) because it is commonly used in applications having machining processes such as shafts and gears. Figure 3 shows the experimental setup used in this study, and high-speed steel (HSS) is used as cutting tools. The workpiece and cutting tool properties are presented in Tables 2 and 3, respectively. The cutting power was calculated based on the cutting force and cutting speed. The cutting forces were measured using homemade dynamometer. Strain gauge dynamometer was used for measuring two cutting force components for a maximum measuring range of 3000 N, with a sensitivity of ± 1 N and natural frequency of 2 KHz. It was calibrated using a proving ring with allowable load of 2920 N with an elastic constant of 1460 N/mm.

An orthogonal external turning was conducted for different cutting conditions using cutting velocity ranged between 30 and 80 m/min, feed ranged between 0.12 and 0.28 mm/rev, and depth of cut ranged between 1 and 2.5 mm. The experimental conditions are shown in Table 3. Full factorial design was carried out where all condition combinations were experimented. The surface roughness was measured using Surtronic 3P (Rank Taylor Hobson Limited).

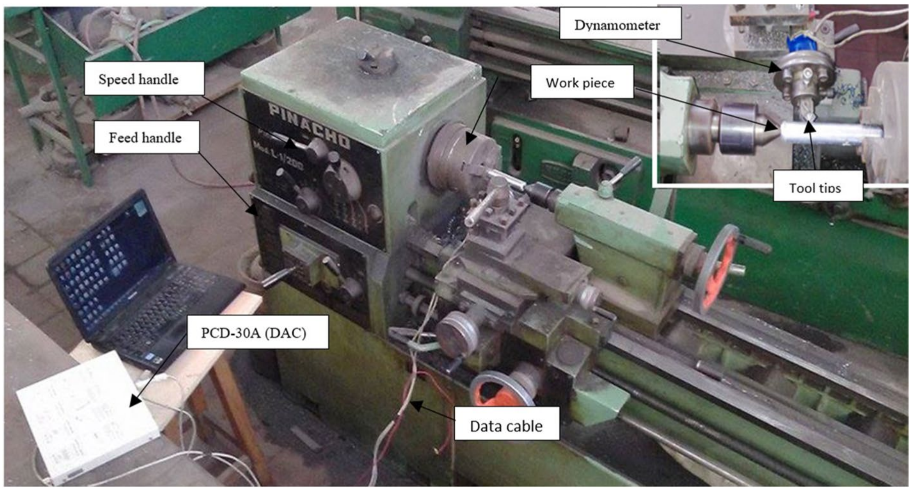


Fig. 3 Used experimental setup

Table 2 Workpiece material properties

Material	Steel 37 (AISI 1025)
Chemical composition	0.2% C, 0.07% P, 0.05% S
Mechanical properties	$UTS = 400$ N/mm^2, yield stress = 240 N/mm^2

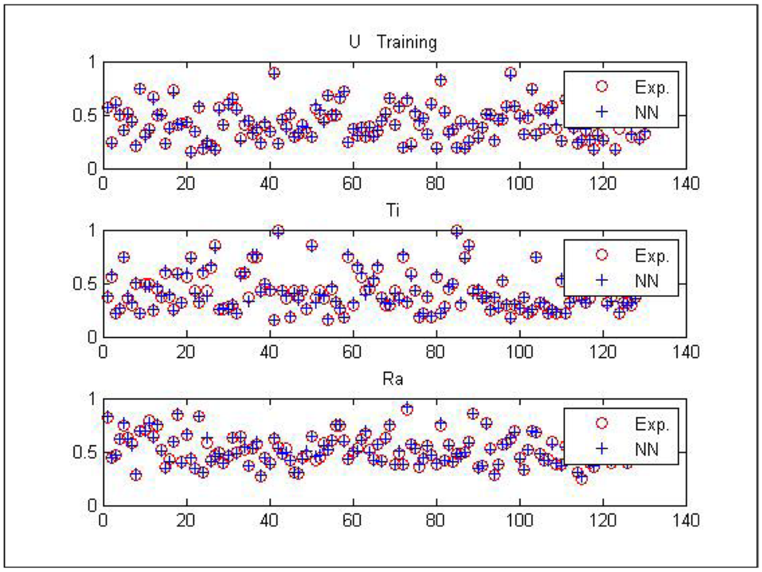
Table 3 Cutting tool properties

Material	Molybdenum high velocity steel tools (AISI M2)					
Chemical Composition	0.85% c, 6% W, 5% Mo, 4% Cr, 2% V					
Hardness	64 Rc					
Cutting tool angles	Rake		Clearance		Approach	
	12°		7°		90°	
Cutting speed (m/min)	30	40	50	60	70	80
Feed rate (mm/rev)	1	1.3	1.6	1.9	2.2	2.5
Depth of cut (mm)	0.12	0.14	0.16	0.2	0.24	0.28

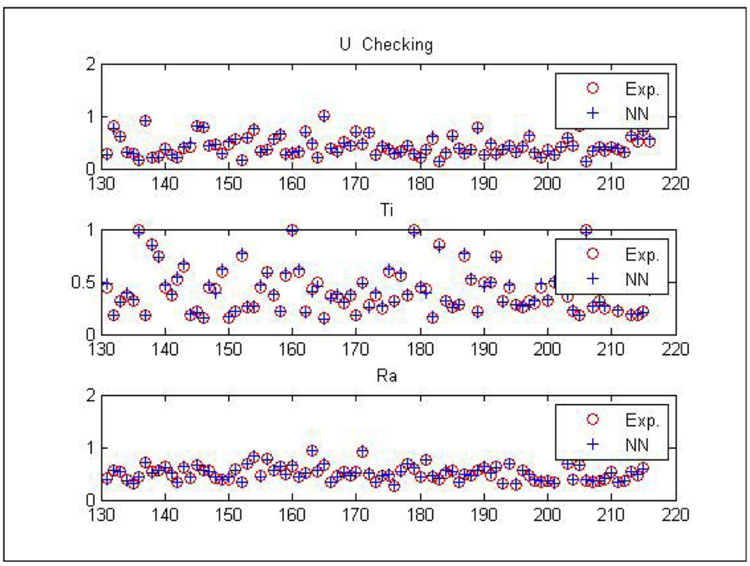
Results and discussion

In this section, the results of the used soft computing technique will be addressed. Customer's demand (number of products "Qp," delivery date "Td," power factor "Ef," quality of product "Q") will be proposed to a factory as values between 0 and 1 depending to how important is each one of these parameters, fuzzy logic as a mapper module implements the fuzzy rules for predicting accurately the weights of PMS output parameters.

The neural network trained and checked experimental data outputs from experiments carried out using conditions in Table 3 with addition to the weights resulted from fuzzy were used by the genetic algorithm for minimizing the cost function. The developed prediction system was found to be capable of accurate PMS output parameters for the range it had been trained as was presented in graphs in Fig. 4a for trained portion of



(a)



(b)

Fig. 4 **a** Trained portion of experimental data. **b** For the checked portion of experimental data

Table 4 Variation of PMS output results with different weights of number of products

Weight of number of products	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
Machining time (min.)	4.57	4.56	4.55	4.57	4.18	3.66	3.71	3.70	3.66	3.63
Power consumed (W)	688	690	690	688	735	818	808	811	817	823
Surface roughness (μm)	2.05	2.05	2.06	2.05	2.16	2.34	2.32	2.32	2.34	2.35

experimental data and Fig. 4b for the checked portion of experimental data. In Fig. 4, the normalized shuffled values of PMS output parameters are plotted in Y-axis for the number of experiments presented in the X-axis.

Table 5 Variation of PMS output results with different weights of quality of product

Weight of quality of product	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
Machining time (min.)	4.58	4.58	4.57	4.59	4.55	4.54	4.57	4.80	5.00	5.59
Power consumed (W)	688	689	690	689	691	691	688	669	654	614
Surface roughness (μm)	2.05	2.06	2.05	2.06	2.06	2.06	2.05	2.06	2.07	2.11

Table 6 Variation of PMS output results with different weights of power factor

Weight of power factor	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
Machining time (min.)	4.56	4.56	4.57	4.55	4.57	12.00	10.90	11.40	12.30	12.80
Power consumed (W)	689	689	688	690	688	333	342	338	331	328
Surface roughness (μm)	2.05	2.05	2.05	2.06	2.05	2.99	3.15	3.08	2.95	2.88

Table 7 Variation of PMS output results with different weights of delivery date

Weight of delivery date	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
Machining time (min.)	4.56	3.91	4.53	4.56	4.56	1.90	2.30	2.30	1.90	1.90
Power consumed (W)	690	775	695	689	690	2460	1310	1320	2460	2460
Surface roughness (μm)	2.05	2.25	2.07	2.05	2.05	5.26	3.24	3.24	5.27	5.27

The experimental conditions shown in Table 3 were used to test and train the neural network model. Then, this model was used to get the optimum conditions shown in Tables 4, 5, 6 and 7 based on new PMS weights which cover a wide range for the customer demand. Tables 4, 5, 6 and 7 show the variation of PMS output results with different weights (importance) of customer's demand. It is clear from Table 4 that as the weight for the number of products increased which means that the customer's demand gives more importance for this aspect, machining time decreased at satisfying power consumption and surface roughness without large increase for the compensation mentioned in the "Methods and experimental work" section. It is obvious from Table 5 that giving of any weight to the quality of product without giving any importance to any other aspects. The surface roughness was sustained at its minimum value at moderate machining time and power consumed. Table 6 shows a decrease of the power consumed to its least value as the weight of power factor increased while the machining time and surface roughness give high values. Finally, Table 7 shows a decrease in the machining time to its least value as the weight of delivery date increased while the power consumed and surface roughness were deteriorated.

The proposed technique was the validated experimental cases shown in Table 8. Table 8 shows running different test problems with different output parameters depending on different customer's demands using the proposed technique.

- In test problem 1, the consumer gave high importance for the quality of product. This leads to lower feed and depth of cut with higher velocity resulting in minimizing the surface roughness to 2.05 μm. The experimental results show minimum surface roughness of 1.9 μm.

Table 8 Experimental results for validation

	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
Customer's demands						
Number of products "Qp"	0.0	0.0	0.0	0.0	0.6	0.5
Delivery date "Td"	0.0	0.0	1.0	0.0	0.0	0.5
Power factor "Ef"	0.0	1.0	0.0	0.6	0.6	0.5
Quality of product "Q"	1.0	0.0	0.0	0.4	0.0	0.5
Cutting conditions						
Feed (mm/rev)	0.12	0.12	0.28	0.12	0.16	0.12
Velocity (m/min)	79.80	30.00	80.00	66.80	79.90	80.00
Depth of cut (mm)	1.00	1.00	2.49	1.00	1.00	1.00
Machining outputs						
Machining time (min.)	4.58	12.80	1.90	5.82	3.71	4.56
Power consumed (W)	687	328	2460	601	807	689
Surface roughness (μm)	2.05	2.88	5.26	2.13	2.32	2.05

- In test problem 2, the consumer gave all the importance for the power factor. This leads to lower feed, velocity, and depth of cut resulting in minimizing the power consumed to 328 W. Experimental results show minimum power consumed of 326 W.
- In test problem 3, the consumer gave all the importance for the delivery date. This leads to higher feed, velocity, and depth of cut resulting in minimizing the machining time to 1.9 min. Experimental results show minimum machining time of 1.9 min.
- In test problem 4, the consumer gave some importance for power factor and quality of product. This leads to lower feed and depth of cut. The velocity decreased than in test problem 1 (from 79.8 to 66.8 m/min) resulting in decreasing power consumed (from 687 to 601 W), but the velocity increased than in test problem 2 for enhancing surface roughness (from 2.88 to 2.13 μm).
- In test problem 5, the consumer gave some importance for the number of products and the power factor. This leads to higher velocity but moderate feed ($f =$ 0.16 mm/rev) for reaching lower machining time of 3.71 min and lower depth of cut to give low-power consumption of 807 W.
- In test problem 6, the consumer gave same importance for all. To discuss all requirements, we have to look to the output globally. High velocity could satisfy the number of products, the delivery date, and the quality of product. Lower feed and depth of cut could satisfy the power factor and the quality of product. Subsequently, reasonable output results were obtained for machining time of 4.56 min, power consumed of 689 W, and surface roughness of 2.05 μm.

As presented, it is obvious that the performance of the combined soft computing technique gives reasonable results when compared with experimental results. Subsequently, more simulations can be conducted for more requirements of customer's demands.

Conclusions

In this research, integrated approach using soft computing was used starting from market customer's demands, passing by optimizing the machining process parameters (PMS), and finally extracting the optimized cutting conditions. The conclusions that can be drawn are summarized as follows:

1. The importance of each of the cutting power consumed, the machining time, and the surface roughness output was considered as a weighted factor based on their customer's demands.
2. The fuzzy mapper module was used to give weights for PMS output based on realistic and reasonable considerations. A neural network was used for controlling the input cutting conditions with the PMS output based on experimental results. Genetic algorithm was formulated for optimization of PMS under certain cutting conditions.
3. The proposed technique was validated using experimental results and gives accurate results.

The variation of PMS output results with different weights (importance) of customer's demand was addressed. Test problems were presented and investigated. As a result, this methodology creates reasonable results for identifying the required input cutting conditions. By implementing market demands, different affecting weights result for the PMS output parameters which give a rich investigations for optimizing these output parameters not only for increasing productivity and quality demands but also for saving power consumed. Test problems show reasonable results when compared to real experimental data.

Abbreviations

PMS	Power, machining time, surface roughness
SC	Soft computing
FL	Fuzzy logic
NN	Neural networks
EC	Evolutionary computation
SA	Simulated Annealing
GA	Genetic Algorithm
Qp	Number of products
Td	Delivery date
Ef	Power factor
Q	Quality of product
Ti	Machining time input
U	Consumed power input
Ra	Surface roughness input
a1	Machining time
a2	Weight of power consumed
a3	The weight of surface roughness

Acknowledgements
Not applicable.

Authors' contributions
The research reported in this paper was conceptualized, and the methodology was suggested by TME and YZ. The manuscript was prepared by TME and AA. The author(s) read and approved the final manuscript.

Funding
This research work is sponsored by the authors.

Availability of data and materials
The datasets are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 7 September 2022 Accepted: 10 January 2023
Published online: 24 January 2023

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