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# MULTI-OBJECTIVE OPTIMISATION OF LASER CUTTING USING CUCKOO SEARCH ALGORITHM

M. MADIĆ*, M. RADOVANOVIĆ, M. TRAJANOVIĆ, M. MANIĆ

Faculty of Mechanical Engineering, Niš, University of Niš, A. Medvedeva 14, 18000, Niš, Serbia
*Corresponding Author: madic@masfak.ni.ac.rs

**Abstract**

Determining of optimal laser cutting conditions for improving cut quality characteristics is of great importance in process planning. This paper presents multi-objective optimisation of the $CO_2$ laser cutting process considering three cut quality characteristics such as surface roughness, heat affected zone (HAZ) and kerf width. It combines an experimental design by using Taguchi's method, modelling the relationships between the laser cutting factors (laser power, cutting speed, assist gas pressure and focus position) and cut quality characteristics by artificial neural networks (ANNs), formulation of the multi-objective optimisation problem using weighting sum method, and solving it by the novel meta-heuristic cuckoo search algorithm (CSA). The objective is to obtain optimal cutting conditions dependent on the importance order of the cut quality characteristics for each of four different case studies presented in this paper. The case studies considered in this study are: minimisation of cut quality characteristics with equal priority, minimisation of cut quality characteristics with priority given to surface roughness, minimisation of cut quality characteristics with priority given to HAZ, and minimisation of cut quality characteristics with priority given to kerf width. The results indicate that the applied CSA for solving the multi-objective optimisation problem is effective, and that the proposed approach can be used for selecting the optimal laser cutting factors for specific production requirements.

Keywords: Cuckoo search algorithm, Multi-objective optimisation, $CO_2$ laser cutting.

## 1. Introduction

Laser cutting is one of the most used thermal-based advanced machining processes in the industry. It is effective method for straight and contour cutting of a wide range of materials with a high degree of dimensional accuracy and surface finish, and is particularly suitable for large batch processing. Laser cutting is realised

**Nomenclatures**

| | |
|---|---|
| $f$ | Focus position, mm |
| $K_w$ | Kerf width, mm |
| $P$ | Laser power, kW |
| $p$ | Assist gas pressure, bar |
| $R_a$ | Average surface roughness, µm |
| $v$ | Cutting speed, m/min |

**Abbreviations**

| | |
|---|---|
| ANN | Artificial neural network |
| CSA | Cuckoo search algorithm |
| DOE | Design of experiment |
| HAZ | Heat affected zone |

by localised heating, melting and evaporation as a result of focusing the laser beam into a very small spot.

Laser cutting is a complex, multifactor machining process. The principal factors that affect the cutting process include [1]: beam power and characteristics, cutting speed, type of assist gas and flow, and focus position. Multiple interaction effects between these factors further complicate cutting process making it difficult to develop relationships between process factors and performance characteristics. The effects of these factors on the laser cutting performances such as cut quality characteristics, productivity and operational costs have been widely studied [2].

Satisfying multiple performance characteristics in laser cutting is of particular interest for manufacturers. However, it could be difficult to achieve all them at the same time, since the laser cutting factors have different contributions on them. Therefore each of these goals is assured only through proper selection of process factors. In real industrial environment it is common practice to select process factor values on the basis of handbooks, manufacturer recommendations and/or previous experience in a trial and error procedure. But, this trial and error approach is high costly in time and labour [3].

To assist in selection of near optimal process factor values various classical and meta-heuristic optimisation techniques were proposed in literature. An effective application of these methods requires accurate mathematical models. An alternative approach for laser cutting optimisation is the application of Taguchi method which requires no mathematical model and is particularly popular for multi-objective optimisation [4-8]. The multi-objective optimisation was done by coupling Taguchi method, through design of experiment and calculation of the appropriate category of the signal to noise ratio, and grey relational analysis or principal component analysis. However, as it is well known, Taguchi method limits the search for the optimal factor settings only on discrete factor values used in the experiment matrix.

Consequently, it is of great importance to exactly quantify the relationships between laser cutting factors and cutting performance characteristics through mathematical modelling and subsequently determinate optimal or near optimal cutting conditions through the use of optimisation algorithms. Ciurana et al. [3] presented an approach for simultaneous minimisation of surface roughness and volume error in pulsed laser micromachining by using artificial neural network (ANN) modelling and particle swarm optimisation algorithm. On the basis of the obtained results the authors concluded that proposed ANN models and swarm optimisation approach are suitable for identification of optimum process settings. In another study in the field of laser micromachining, Dhupal et al. [9] developed mathematical models based on ANNs and response surface methodology for correlating responses such as the upper width, lower width and depth of the microgroove and different laser input process factors. Subsequently, multi-objective optimisation analysis was performed to achieve the target value of all three responses. Recently, Pandey and Dubey [10] presented an approach for simultaneous optimisation of kerf taper and surface roughness in the Nd:YAG laser cutting of titanium alloy sheet using regression models and genetic algorithm. The applied hybrid approach resulted in the improvements of 19.16% and 17.32% in kerf taper and surface roughness, respectively, i.e., overall improvement of 18% has been registered in multiple quality characteristics.

The present paper deals with multi-objective optimisation of the laser cutting process considering three cut quality characteristics such as surface roughness, HAZ and kerf width. Four cutting factors, laser power, cutting speed, assist gas pressure and focus position were considered in the experiment which was planned and conducted according to the Taguchi's experimental design using the $L_{27}$ orthogonal array. Using the obtained experimental data, three ANN prediction models were developed in order to explicitly express the relationships between the laser cutting factors and the cut quality characteristics. Multi-objective optimisation problem was formulated using the weighting sum method. This paper presents the application of novel meta-heuristic optimisation algorithm cuckoo search algorithm [11] for solving multi-objective optimisation problem. Optimisation results with corresponding optimal values of laser cutting factors were presented for four different combinations of weighting factors.

## 2. $CO_2$ Laser Cutting Experiment

Taguchi experimental designs provide an efficient plan to study the entire experimental region of interest for the experimenter with the minimum number of trials as compared with the classical DOE, therefore it was chosen for performing the laser cutting experiment [12]. They can be efficiently used for the analysis of a number of process factors and their interactions. Moreover, the implementation of these experimental plans enables process optimisation by Taguchi's optimisation methodology. Finally, the use of orthogonal arrays can significantly reduce the number of ANN training data without affecting too much the accuracy of the ANN prediction [13].

The laser cutting experiment was performed by means of ByVention 3015 (Bystronic) $CO_2$ laser delivering a maximum output power of 2.2 kW at a wavelength of 10.6 μm, operating in continuous wave mode. The cuts were performed with a Gaussian distribution beam mode ($TEM_{00}$) on a 3 mm thick AISI 304 stainless steel using a focusing lens of focal length of 127 mm. The conical shape nozzle (HK20) with inner diameter of 2 mm was used. The nozzle-workpiece stand-off distance was controlled at 1 mm. In this study nitrogen with purity of 99.95% was used as assist gas.

Four laser cutting factors at three levels such as laser power ($P$), cutting speed ($v$), assist gas pressure ($p$) and focus position ($f$) were taken as input variables. These factors were arranged in the standard $L_{27}$ ($3^{13}$) Taguchi's orthogonal array to columns 1, 2, 5 and 9, respectively. Twenty-seven samples were cut according with a combination of laser cutting factors listed in Table 1.

**Table 1. Combination of the laser cutting factors for each experimental trial.**

| Trial | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***P*** (kW) | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 |
| ***v*** (m/min) | 2 | 2 | 2 | 2.5 | 2.5 | 2.5 | 3 | 3 | 3 | 2 | 2 | 2 | 2.5 | 2.5 |
| ***p*** (bar) | 9 | 10.5 | 12 | 9 | 10.5 | 12 | 9 | 10.5 | 12 | 9 | 10.5 | 12 | 9 | 10.5 |
| ***f*** (mm) | −2.5 | −1.5 | −0.5 | −1.5 | −0.5 | −2.5 | −0.5 | −2.5 | −1.5 | −1.5 | −0.5 | −2.5 | −0.5 | −2.5 |
| **Trial** | **15** | **16** | **17** | **18** | **19** | **20** | **21** | **22** | **23** | **24** | **25** | **26** | **27** | |
| ***P*** (kW) | 1.8 | 1.8 | 1.8 | 1.8 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | |
| ***v*** (m/min) | 2.5 | 3 | 3 | 3 | 2 | 2 | 2 | 2.5 | 2.5 | 2.5 | 3 | 3 | 3 | |
| ***p*** (bar) | 12 | 9 | 10.5 | 12 | 9 | 10.5 | 12 | 9 | 10.5 | 12 | 9 | 10.5 | 12 | |
| ***f*** (mm) | −1.5 | −2.5 | −1.5 | −0.5 | −0.5 | −2.5 | −1.5 | −2.5 | −1.5 | −0.5 | −1.5 | −0.5 | −2.5 | |

Cut quality obtained was assessed in terms of average surface roughness ($R_a$), width of HAZ, and top kerf width ($K_w$). Surface roughness measurement was taken along the cut at approximately the middle of the thickness using a Surftest SJ-301 (Mitutoyo) profilometer. Top kerf width and width of HAZ were measured using the optical microscope (Leitz, Germany). All measurements were repeated three times to obtain averaged values.

## 3. Multi-objective Optimisation

In laser cutting there are often more than one objective or criteria, and usually these multiple objectives conflict with each other. For example, it is often required to obtain high cut quality while maximising the material removal rate and minimising cost. Such kind of optimisation problems are the subject of multi-objective optimisation and can generally be formulated as:

$$\begin{aligned} &Minimize: f(x) = [f_1(x), f_2(x), ..., f_m(x)]^T \\ &subject\ to: g_j(x) \le 0;\ j = 1, ..., n \end{aligned} \quad (1)$$

where $\boldsymbol{x}$ is a vector of design variables, $m$ is the number of objective functions and $n$ is the number of inequality constraints.

In general, no solution vector $\boldsymbol{x}$ exists that minimises all the $m$ objective functions simultaneously. Hence, a concept of the Pareto optimum solution is used in multi-objective optimisation problems. A solution point for problem formulated in Eq. (1) is Pareto optimal if and only if it is not possible to move from that point and improve at least one objective function without detriment to any other objective function [14]. The set of all Pareto solutions of a multi-objective optimisation problem is known as the Pareto frontier (or Pareto set).

The most widely used method for multi-objective optimisation is the weighted sum method [15]. The method transforms multiple objectives into an aggregated single objective function by multiplying each objective function with a weighting factor and summing up all contributors:

$$f_{\text{weightedsum}} = w_1 \cdot f_1 + w_2 \cdot f_2 + \ldots + w_m \cdot f_m \tag{2}$$

where $w_i$ ($i = 1,\ldots,m$) is a weighting factor for the $i$-th objective.

Such a scalar function is often referred to as the preference function or utility function [16]. This approach is called a priori approach since the user is expected to provide the weighting factor values. The relative value of the weighting factors reflects the relative importance of the objectives. If $\sum_{i=1}^{m} w_i = 1$ and $0 \le w_i \le 1$, then the weighted sum is said to be a convex combination of objectives [15]. If all of the weighting factors are positive, then minimising Eq. (2) provides a sufficient condition for Pareto optimality, which means the minimum of Eq. (2) is always Pareto optimal [14]. With systematic variation in weighting factor values, minimising the weighted sum can yield all of the Pareto optimal points if the considered multi-objective optimisation problem is convex [17].

## 4. Cuckoo Search Algorithm

Cuckoo search algorithm (CSA) is a novel population based stochastic global search meta-heuristic algorithm developed by Yang and Deb [11]. CSA is inspired by natural mechanisms and mimics the breeding behaviour of some cuckoo species that lay their eggs in the nests of host birds. Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The goal is to use new and potentially improved solutions (cuckoos) to replace worse solutions in the nests. CSA can be briefly described using the following three idealised rules [18]:

- Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest.
- The best nests with high quality of eggs (solutions) will carry over to the next generations.
- The number of available host nests is fixed, and a host can discover an alien egg with a probability $p_a \in [0, 1]$. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

An important issue is the applications of Levy flights and random walks for generating new solutions $x_i^{(t+1)}$ [11]:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus Levy(\lambda) \tag{3}$$

where $\alpha$ ($\alpha$>0) represents a step size. The product $\oplus$ means entry-wise multiplications.

The random step length is drawn from a Lévy distribution which has an infinite variance with an infinite mean [11]:

$$Levy \sim u = t^{-\lambda},\ \lambda \in (0,3] \tag{4}$$

The salient feature of the CSA is its ability to find all the optima simultaneously if the number of nests is much higher than the number of local optima. As noted by Yang and Deb [11] this advantage may become more significant when dealing with multi-objective optimisation problems. The main control parameters of the CSA include the number of host nests (or the population size $n$) and the probability $p_a$. From the analysis of the CSA performance, Yang and Deb [11] observed that $n$ = 15 to 25 and $p_a$ = 0.15 to 0.30 are sufficient for most optimisation problems.

CSA has been applied to solve various benchmark and engineering optimisation problems and the results indicate that CSA performs superior to different existing algorithms. For more details the reader should refer to existing literature on CSA and its implementation [11, 18-22].

## 5. Results and Discussion

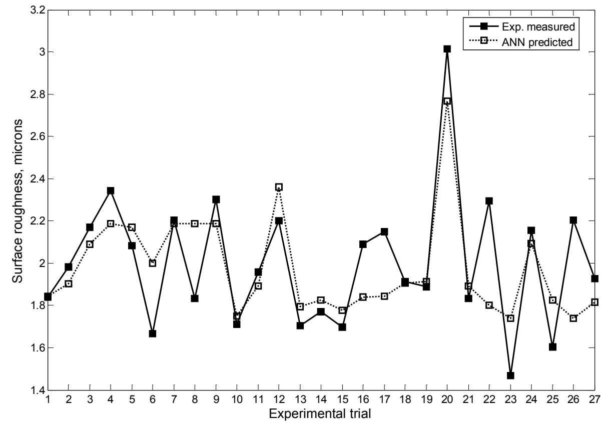
### 5.1. Mathematical functions of the cut quality characteristics

ANN is one of the most popular nonlinear mapping systems with ability to model complex processes with many interactions between multiple inputs and outputs using the experimental data. In this paper, for ANN modelling, three cut quality characteristics, $R_a$, HAZ and $K_w$, are considered as the output variables. In order to have an accurate models, three separate ANN models were used for relating input variables consisting of laser power ($P$), cutting speed ($v$), assist gas pressure ($p$) and focus position ($f$), and cut quality characteristics.

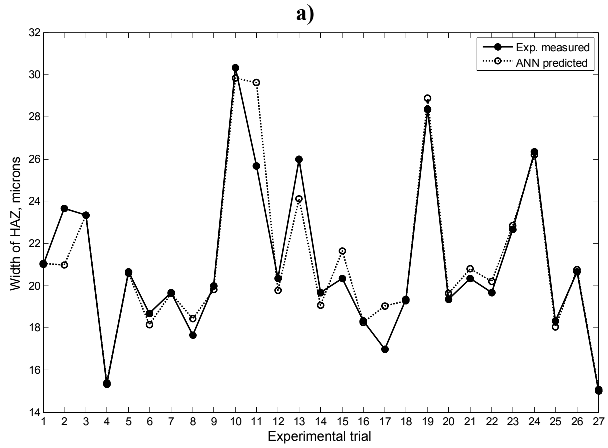
Three ANN models with four input neurons, three hidden neurons and one neuron in output layer, have been developed using the MATLAB. The architecture of the ANN models was selected considering the total number of connection weights biases in the ANN as well as the available number of data for training. Hyperbolic tangent sigmoid and linear transfer functions were used in hidden layer and output layer, respectively. In order to faciliate ANN training process, the experimental data was normalised in the range [−1, 1].

In order to determine the connection weights and biases of the ANN models, the training process was carried out using Levenberg-Marquardt training algorithm by using randomly selected 19 out of 27 sets of input/output experimental data and the rest was used for testing the ANNs performance. The ANNs training was stopped by considering the well known bias-variance trade-off in model development. The comparison between experimental and predicted values for the cut quality characteristics is shown in Fig. 1.

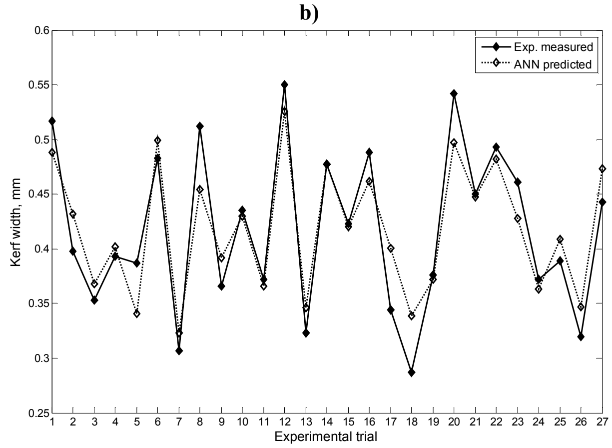
From the analysis of the Fig. 1, one can observe that particular combination of laser cutting factors variously affects the cut quality characteristics. A given combination of the laser cutting factor settings results in enhancement of one of the cut quality characteristics but decreases the other cut quality characteristics, raising the need for multi-objective optimisation. As seen, in most cases, for both training and testing data, the experimental and predicted values are in good agreement.




**a)**




**b)**




**c)**

**Fig. 1. Experimental results and comparison with the ANN models predictions.**

The estimated mean absolute percentage errors of the ANN models were obtained as:

- for surface roughness ANN model: 8.71% and 9.66% on training and testing data respectively,
- for HAZ ANN model: 1.26% and 7.3% on training and testing data respectively,
- for kerf width ANN model: 5.5% and 6.5% on training and testing data respectively.

The obtained results suggest that the developed ANN models can be used to acquire a function that maps laser cutting factors and the cut quality characteristics in a range considered in the experiment and they can be used to optimise the $CO_2$ laser cutting process.

### 5.2. Multi-objective optimisation of $CO_2$ laser cutting

In multi-objective optimisation of the $CO_2$ laser cutting process, instead of treating the responses separately, all three of them are optimised simultaneously. Using the weighted sum method, the following objective function is developed:

$$z = w_1 \cdot R_a + w_2 \cdot HAZ + w_3 \cdot K_w \tag{5}$$

where $w_1$, $w_2$ and $w_3$ are weighting factors decided based on the priorities among the various responses to be simultaneously optimised.

In the present investigation, weighting factors of 0.33 for each of the responses are considered (case I: $w_1$=$w_2$=$w_3$=0.333), which gives equal priorities for all three cut quality characteristics for simultaneous optimisation. Also, three additional combinations of weighting factors are given consideration, that is: case II: $w_1$=0.5, $w_2$=0.25 and $w_3$=0.25 (priority given to surface roughness); case III: $w_1$=0.25, $w_2$=0.5 and $w_3$=0.25 (priority given to HAZ); and case IV: $w_1$=0.25, $w_2$=0.25 and $w_3$=0.5 (priority given to kerf width). Note that the estimations of the $R_a$, HAZ and $K_w$ in Eq. (5) are based on ANN models developed with the scaled input/outputs in the range [−1, 1]. Also, according to the experimental investigation in this study, the limits on the input variables of laser power ($P$), cutting speed ($v$), assist gas pressure ($p$) and focus position ($f$) are: $1.6 \leq P \leq 2$ kW, $2 \leq v \leq 3$ m/min, $9 \leq p \leq 12$ bar and $-2.5 \leq f \leq -0.5$ mm.

### 5.3. Optimisation results

For solving the multi-objective optimisation problem formulated in Eq. (5), MATLAB computer code was developed so as to integrate ANN models with the CSA. Due to the fact that different initial populations affect directly to the final result, a series of simulation runs are done to obtain best results. Running the simulations for 50 times it was found that the best results are obtained using the $n$=25 and $p_a$=0.25. The results obtained after solving the multi-objective optimisation using the CSA algorithm are shown in Table 2.

As seen from Table 2, for all four cases considered, high cutting speed is preferable. On the other hand, depending on the weighting factors, combination of high laser power and high assist gas pressure or combination of low laser power and low assist gas pressure yield optimal results. Also, focusing the laser beam up to 1/3 of material thickness is beneficial for all four cases considered.

**Table 2. Multi-objective optimisation results.**

| | Input variables | | | | Output variables | | |
|---|---|---|---|---|---|---|---|
| | ***P*** [kW] | ***v*** [m/min] | ***p*** [bar] | ***f*** [mm] | $R_a$ [μm] | ***HAZ*** [μm] | $K_w$ [mm] |
| **Case I** | 1.6 | 2.94 | 9.53 | –0.72 | 2.190 | 13.61 | 0.338 |
| **Case II** | 2 | 3 | 11.86 | –0.5 | 1.653 | 17.03 | 0.349 |
| **Case III** | 1.6 | 2.89 | 9.17 | –1 | 2.188 | 12.57 | 0.356 |
| **Case IV** | 1.6 | 3 | 9.8 | –0.5 | 2.187 | 14.60 | 0.325 |

Under the optimal laser cutting factor settings for case study 2, in the confirmation experiment trial the following values for cut quality characteristics were obtained: $R_a$ = 1.834 μm, HAZ = 18.92 μm and $K_w$ = 0.326 mm. By comparing these results with ANN predictions for optimal values of $R_a$ = 1.653 μm, HAZ = 17.03 μm and $K_w$ = 0.349 mm, as determined by the CSA, one can observe differences of 9.86%, 10.52% and 6.6%, respectively, which approximately correspond to the prediction accuracy of the developed ANNs. Considering statistical assessments of all ANN mathematical models, one can expect similar differences in optimisation results and experimental values for cut quality characteristics for other case studies.

## 6. Conclusions

In this paper, multi-objective optimisation of the cut quality characteristics such as surface roughness, width of HAZ and kerf width in $CO_2$ laser cutting of stainless steel was presented. The applied methodology integrates modelling of the relationships between the laser cutting factors (laser power, cutting speed, assist gas pressure and focus position) and cut quality characteristics using ANNs, formulation of the multi-objective optimisation problem using weighting sum method and solving it by CSA.

From the analysis of the effect of the laser cutting factors on the cut quality characteristics the following was observed: (*i*) cut quality characteristics are highly sensitive to variation of laser cutting factors, (*ii*) there is no best combination of the laser cutting factors which improves all three cut quality characteristics at the same time, (*iii*) focusing the laser beam up to 1/3 of material thickness is beneficial for improving cut quality.

In the context of multi-objective optimisation of cut quality characteristics, the optimal laser cutting factors dependent on the importance order of the cut quality characteristics were determined for four cases. The results indicate that the applied CSA approach for solving the multi-objective optimisation problem with conflicting objectives is efficient. Based on the specific production requirements, the presented methodology is applicable for determining a set of optimal laser cutting factor settings for improving cut quality characteristics in $CO_2$ laser cutting.

In conclusion, the ANN based process modelling and multi-objective optimisation approach developed in this work will provide an effective and flexible tool to a process engineer to choose optimal laser cutting factors for improving multiple cut quality characteristics in the $CO_2$ laser cutting process.

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## References

1. Asibu, E.K. (2009). *Principles of laser material processing*. Wiley, New Jersey.
2. Dubey, A.K.; and Yadava, V. (2008). Laser beam machining - A review. *International Journal of Machine Tools and Manufacture*, 48(6), 609-628.
3. Ciurana, J.; Arias, G.; and Özel, T. (2009). Neural network modelling and particle swarm optimisation (PSO) of process parameters in pulsed laser micromachining of hardened AISI H13 steel. *Materials and Manufacturing Processes*, 24(3), 358-368.
4. Dubey, A.K.; and Yadava, V. (2008). Multi-objective optimisation of laser beam cutting process. *Optics & Laser Technology*, 40(3), 562-570.
5. Çaydaş, U.; and Hasçalık, A. (2008). Use of the grey relational analysis to determine optimum laser cutting parameters with multi-performance characteristics. *Optics & Laser Technology*, 40(7), 987-994.
6. Dubey, A.K.; and Yadava, V. (2008). Multi-objective optimisation of Nd:YAG laser cutting of nickel-based superalloy sheet using orthogonal array with principal component analysis. *Optics and Lasers in Engineering*, 46(2), 124-132.
7. Sharma, A.; Yadava, V.; and Rao, R. (2010). Optimisation of kerf quality characteristics during Nd: YAG laser cutting of nickel based superalloy sheet for straight and curved cut profiles. *Optics and Lasers in Engineering*, 48(9), 915-925.
8. Pandey, A.K.; and Dubey, A.K. (2012). Taguchi based fuzzy logic optimisation of multiple quality characteristics in laser cutting of duralumin sheet. *Optics and Lasers in Engineering*, 50(3), 328-335.
9. Dhupal, D.; Doloi, B.; and Bhattacharyya, B. (2007). Optimisation of process parameters of Nd:YAG laser microgrooving of Al2TiO5 ceramic material by response surface methodology and artificial neural network algorithm. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 221(8), 1341-1350.
10. Pandey, A.K.; and Dubey, A.K. (2012). Simultaneous optimisation of multiple quality characteristics in laser cutting of titanium alloy sheet. *Optics & Laser Technology*, 44(6), 1858-1865.
11. Yang, X.S.; and Deb, S. (2010). Engineering optimisation by cuckoo search. *International Journal of Mathematical Modelling and Numerical Optimisation*, 1(4), 330-343.

12. Madić, M.; and Radovanović, M. (2012). An artificial intelligence approach for the prediction of surface roughness in $CO_2$ laser cutting. *Journal of Engineering Science and Technology*, 7(6), 679-689.
13. Chang, C.C.; Chang, T.Y.P.; Xu, Y.G.; and To, W.M. (2002). Selection of training samples for model updating using neural networks. *Journal of Sound and Vibration*, 249(5), 867-883.
14. Marler, T.; and Arora, J.S. (2005). Function-transformation methods for multi-objective optimisation. *Engineering Optimisation*, 37(6), 551-570.
15. Kim, I.Y.; and De Weck, O.L. (2006). Adaptive weighted sum method for multiobjective optimisation: a new method for Pareto front generation. *Structural and Multidisciplinary Optimisation*, 31(2), 105-116.
16. Yang, X.S. (2008). *Introduction to mathematical optimisation - from linear programming to metaheuristics*. Cambridge International Science Publishing.
17. Miettinen, K. (1999). *Nonlinear multiobjective optimisation*. Kluwer Academic Publishers, Boston.
18. Yang, X.S.; and Deb, S. (2009). Cuckoo search via Lévy flights. *In Proceedings of World Congress on Nature & Biologically Inspired Computing. IEEE Publications*, 210-214.
19. Gandomi, A.H.; Yang, X.S.; and Alavi, A.H. (2012). Cuckoo search algorithm: a metaheuristic approach to solve structural optimisation problems. *Engineering with Computers*, 29(1), 17-35.
20. Rajabioun, R. (2011). Cuckoo optimisation algorithm. *Applied Soft Computing*, 11(8), 5508-5518.
21. Yildiz, A.R. (2013) Cuckoo search algorithm for the selection of optimal machining parameters in milling operations. *International Journal of Advanced Manufacturing Technology*, 64(1), 55-61.
22. Bulatović, R.R.; Đorđević, S.R.; and Đorđević, V.S. (2013). Cuckoo search algorithm: a metaheuristic approach to solving the problem of optimum synthesis of a six-bar double dwell linkage. *Mechanism and Machine Theory*, 61, 1-13.