

APPLICATION OF THE TAGUCHI METHOD FOR OPTIMIZATION OF LASER CUTTING: A REVIEW

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ABSTRACT: Laser cutting is one of the most widely used thermal based non-contact advanced machining process. Considerable research studies were aimed at optimization of laser cutting process performance. The common approaches to tackle optimization problems in laser cutting include analytical approach, empirical approaches based on regression analysis, response surface methodology and artificial neural networks, and modeless approach using Taguchi method. In this paper a brief overview of the Taguchi method with the key concepts and tools used in the method are given. After the analysis of the parameters and performance characteristics of laser cutting process, the paper reviews the research work focused on the application of the Taguchi method for optimization of laser cutting. The search for papers was conducted using scientific resource bases considering publications in last years. The paper provides summary analysis of the findings, identifies trends in the literature and discusses the issues that need to be addressed.
KEY WORDS: CO_2 laser cutting, Taguchi method, optimization, review

1 INTRODUCTION

Laser cutting is a thermal based process effective for contour cutting of different materials. It is widely used non-conventional machining process in industry due to its advantages of high cut quality and cost effectiveness in large batch production. Numerous advantages such as convenience of operation, high precision, small heat-affected zone (HAZ), minimum deformity, low waste, low level of noise, flexibility, ease of automation etc. along with technological improvements in laser cutting machines, made laser cutting technology more prevalent in today's production systems [4].

Laser cutting is a complex process with numerous parameters which in consort have essential role on the process performance. In today's competitive market, manufacturers using laser cutting technology strive to increase productivity performance such as cutting speed, productivity and processing time, and also to decrease manufacturing costs. Satisfying multiple performance call for mathematical modeling of the laser cutting process and subsequently determination of acceptable (near optimal) cutting conditions through the use of optimization methods.

Considerable research studies have been carried out to analyze laser cutting process [5]. Different methodologies were employed for modeling the laser cutting process such as analytical methods, multiple regression analysis (MRA) [6, 7], response surface methodology (RSM) [8, 9], fuzzy expert systems [10], and artificial neural networks (ANNs) [11-14]. Subsequently, the near optimal laser processing conditions were identified by applying classical optimization algorithms or metauristic algorithms like genetic algorithms, simulated annealing and particle swarm optimization. These methods are powerful tools for systematic modeling, analysis and optimization. However, they are time and computationally expensive and require a considerable knowledge in mathematical modeling, optimization theory, statistics and artificial intelligence.

From the other hand, the application of the Taguchi method (TM) without formulation of any kind of model is an attractive alternative for determining near optimal cutting parameter settings in laser cutting and is being increasingly applied. The method proved efficient, yet relatively simple and became particularly popular when dealing with multiple performance characteristics. By using the Taguchi technique, industries are able to greatly reduce product development cycle time for both design and production and thus reducing costs and increasing profit [15].

This paper reviews research work on the application of the TM in optimization of laser cutting process, spanning for last five years. The search for papers was conducted using scientific resource bases, such as Elsevier, Springer, Taylor and Francis, Emerald, and others. Section 2 provides a brief outline of the TM, and the applications of TM for optimization of laser cutting are presented in Section 3. In this section, parameters and performance characteristics of laser cutting are categorized and the reviewed papers were analyzed. Section 4 presents the conclusions and points to directions for future research on the subject.

2 TAGUCHI METHOD: AN OVERVIEW

Driven by the need to compete on price and performance and to maintain profitability, quality conscious manufacturers are increasingly aware of the need to optimize products and processes. Quality achieved by means of design optimization is found by many manufacturers to be cost effective in gaining and maintaining a competitive position in the world market [1].

The TM is a well-known, unique and powerful technique for product/process quality improvement. It is widely used for analysis of experiment and product or process optimization. The application of the TM is not limited to any specific problem [16]. The Taguchi approach has been successfully applied in many industrial organizations and has completely changed their outlook on quality control [1].

Taguchi in his off-line quality control strategy proposed that optimization of a process or product should be carried out in a three-step approach: system design, parameter (factor) design, and tolerance design. The parameter (factor) design is the key step in the TM for achieving high quality characteristics, without increasing cost. The objective of this step is to optimize the settings of the process parameter values as close as possible to the target paramete values, with minimum variation. Hence, the TM belongs to the so called robust design [1, 2, 16]. This methodology allows for efficient identification of optimal setting of the control parameters (factors) making the product/process insensitive to the noise factors [2]. Noise factors (external conditions, manufacturing imperfections, etc.) are unwanted sources of variation and can be uncontrollable or too expensive to control. These factors are usually ignored in the classical design of experiment (DOE) approach. Two major tools used in the TM are orthogonal arrays (OAs) and signal to noise (S/N) ratios.

In the TM to study the entire parameter space with minimum number of experiments, an OA, which is a small fraction of full factorial design, is used. The array is called orthogonal because for every pair of parameters all combinations of parameter levels occurs an equal number of times. There are three types of the OAs, those that deal with two-level parameters, those that deal with three-level parameters, and those that deal with mixed-level parameters. The TM is usable when the control and noise parameters are all quantitative (continuous), all qualitative (discrete), or mixed. Moreover, this method may include qualitative (discrete) quality characteristics [16]. The orthogonality of a design matrix is not lost by keeping one or more columns of an OA empty. Thus, the design matrix formed by remaining columns is also an OA. There are different techniques for modifying OAs (dummy-level technique, compound factor method, column merging method, branching design, etc.) [1, 2]. Each row of an OA represents one trial with the levels of different parameters in that trial. The number of rows must be at least equal to the total degrees of freedom required for the experiment. Each column of an OA represents one parameter and its setting levels in each trial. Some of the columns represent the interactions among the control parameters. Columns for all of the OAs interactions are designated in the original design matrix, triangular interaction tables, and linear graphs. Each linear graph must be consistent with the triangular interaction table of an OA [16]. The different linear graphs are useful for design of experiments having various requirements [1-3].

Traditionally, data from experiments are directly used to analyze the mean response. However, Taguchi suggested a summary statistic that combines information about the mean and variance into a single performance measure, known as the signal-to-noise (S/N) ratio. Taguchi found out empirically that S/N ratios give the (near) optimal combination of the parameter levels, where the variance is minimum, while keeping the mean close to the target value, without using any kind of model [16]. Depending on the criterion for the quality characteristic to be optimized, different S/N ratios can be chosen [2, 3]:

a) smaller-the-better,

$$\eta \equiv S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

b) larger-the-better,

$$\eta \equiv S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{2}$$

c) nominal-the-best,

$$\eta \equiv S/N = 10\log\left(\frac{\overline{y}^2}{s^2}\right) \tag{3}$$

where y_i is the i-th observed value of the response (quality characteristic), n is the number of observations in a trial, $\overline{y}$ is the average of observed values (response) and s is the variance.

Regardless of the category of the performance characteristic, the larger algebraic value of S/N ratio corresponds to the better performance characteristic, and hence the optimal level of the parameter is the level with the highest S/N.

In the TM the results of the experiments are analyzed to achieve one or more of the following three objectives [1]:

1. To establish the best or the optimum condition for a products or a process
2. To estimate the contribution of individual parameters
3. To estimate the response under the optimum conditions

The optimum condition is identified by studying the main effects of each of the parameters using the analysis of means (ANOM). For example, the mean S/N ratio of parameter Q at level k can be calculated as [16]:

$$average\left(S/N\right)_{Q_k} = \frac{1}{n_{Q_k}} \sum_{l=1}^{n_{Q_k}} \left[\left(S/N\right)_{Q_k}\right]_l \tag{4}$$

where n_{Q_k} is the number of appearances of parameter Q at level k in Taguchi's matrix, and $\left(S/N\right)_{Q_k}$ is the S/N ratio related to parameter Q at level k.

The Taguchi analysis provides a pre-established experimental set of the sizes which can determine the effects and the interaction of the considered parameters [17]. The knowledge of the contribution of individual parameters is a key to deciding the nature of the control to be established on a production process [1]. The analysis of variance (ANOVA) is the statistical tool most commonly applied to investigate which design parameters and their interactions affect the response significantly. Based on the experimental results it aims at determining the percentage contribution of each parameter. The final step in analyzing the experimental results is the verification of the improvement of the quality characteristic. For that purpose, a confirmation experiment should be carried out implying the (near) optimal levels of the design parameters.

The predicted S/N ratio using the optimal levels of the design parameters ($\hat{\eta}_{opt}$) can be calculated as [1-3]:

$$\hat{\eta}_{opt} = \overline{\eta} + \sum_{i=1}^{p}\left(\overline{\eta}_{i,opt} - \overline{\eta}\right) \tag{5}$$

where $\overline{\eta}$ is the total mean S/N ratio, $\overline{\eta}_{i,opt}$ is the mean S/N ratio for i-th design parameter at the optimal level, and p is the number of design parameters that significantly affect the quality characteristic.

The total mean S/N ratio for an experiment is calculated by equation:

$$\overline{\eta} = \frac{1}{n_t}\sum_{i=1}^{n_t}\eta_i \tag{5}$$

where n_t is the total number of trials, and η_i is the S/N ratio in i-th trial in the OA.

Taguchi suggests two different routes to carry out the complete analysis [1]:

- standard approach, where the results of a single run, or the average of repetitive runs, are processed through main effect and ANOVA analyses, and
- the second approach, which he strongly recommends for multiple runs, is to use S/N ratio for the same steps in the analysis. S/N analysis determines the most robust set of operating conditions from variations within the results.

As it is well known, the TM limits the optimization to the specific levels of parameter values. However, some intermediate combination of parameter values may exist, which would yield better results. In most cases, the optimal parameter settings obtained by the TM is not the exact optimal solution, but the near optimal solution. Although TM belongs to the technique of single-criterion optimization there are different approaches in multiple-objective optimization using TM [18-20]. A novel approach to multi-objective process optimization, based on the TM and artificial intelligence has been proposed [21].

3 APPLICATION OF THE TM FOR OPTIMIZATION OF LASER CUTTING

3.1 Laser cutting parameters

Laser cutting is a complex process in which a number of controllable and uncontrollable parameters have essential role on the process performance. Laser parameters can be broadly classified into:

1. Laser cutting system parameters,
2. Workpiece parameters, and
3. Laser process parameters.

Laser cutting system parameters are those related to the type of laser cutting machine (wavelength, maximal output power, mode, spatial and temporal distribution of power, power stability), laser beam (diameter of the laser beam, laser beam quality (M2) factor, polarization), cutting head (focusing system, nozzle construction, nozzle diameter) and coordinate work table (table positioning accuracy, precision of movement, spatial mobility). Workpiece parameters define the geometry (shape contour, size, complexity, tolerance) and thermal, optical, mechanical, chemical, electrical properties of the material to be cut by laser. Laser process parameters can be divided into variable such as laser power, cutting speed and assist gas pressure, and constant such as focus position, type and purity of the assist gas, nozzle diameter and nozzle-workpiece stand off distance. In real manufacturing environment cutting speed, laser power and assist gas pressure are parameters mostly considered by laser cutting machine operators as a means of intermediate intervention during laser processing. Actually, cutting speed, laser power and assist gas pressure are easily controlled and can change during laser processing operation for achieving desired effect.

3.2 Laser cutting performances

In laser cutting there are several performance indicators by which conclusions can be made about the adequacy of the selected process parameters as well as on the appropriateness on using laser cutting process. The performance of laser cutting can be seen as technological and techno-economic objective functions and grouped into four main categories:

1. Process performance (cutting speed, specific cutting energy, specific power consumption, nozzle wear),
2. Quality performance (kerf width, taper, surface roughness, dross attachment),
3. Productivity performance (specific cutting speed, productivity, processing time), and
4. Economic performance (costs).

The trend in the industrial applications of laser cutting technology is to increase the quality of the cut while maintaining high cutting speed. In addition, to sustain in competitive markets, manufacturers using laser cutting technology are forced to decrease lead time and product price as well as to offer customized products. In order to be cost efficient method for batch processing, the variations of the product/process quality need to be low. Therefore, the goal that arises is to minimize the effects of uncontrollable (noise) parameters so that cut tolerance is low and the part repeatability is high.

3.3 Selection of laser cutting conditions

Laser cutting performances change drastically with the laser cutting process parameter settings. Via appropriate selection of laser process parameters, process performances can be improved considerably. However, the (near) optimum parameter settings for one process performance may deteriorate other process performances. Satisfying different requirements call for mathematical modeling of laser cutting process and subsequently determination of the (near) optimal cutting conditions through the use of optimization algorithms. Although through integration of mathematical models (analytical, empirical or semi-empirical based on artificial intelligent techniques) with classical or modern optimization methods like metaheuristic algorithms yield acceptable results, these techniques are complex and more time and computationally expensive.

To overcome this problem, researches applied the TM which provides a systematic, efficient and easy-to-use approach for the process optimization. The robust design methodology, proposed by Taguchi, has become the most preferable method for identifying the near optimal laser cutting conditions. The application of TM in the field of laser cutting is reviewed in the following section.

3.4 Characterization of reviewed works

The search for papers was conducted using scientific resource bases considering publications in last five years. Publications were chosen for evaluation if they matched the following requirements:

- focused on laser cutting process,
- made use of the TM as optimization technique.

Based on these criteria, 10 publications were selected and reviewed. Figure 1 depicts their chronological distribution. The figure shows that application of the TM for optimization of laser cutting has attracted a sustained interest from researchers, however the most papers were published in 2008.

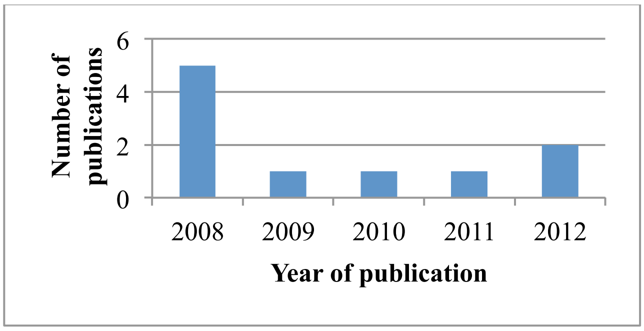

Figure 1. Yearly distribution of reviewed publications.

Table 1 synthesizes distinct laser process parameters taken by authors along reviewed papers. The table shows type of laser system used, considered (input) laser process parameters, OA used for experimental matrix, type of assist gas used, laser performance (outputs) examined, and workpiece material. In addition to that, information is provided on whether the TM was used for single or multi-objective optimization.

It is seen that considerable research studies were carried out to improve the performances of Nd:YAG laser cutting whereas the application of the TM for optimization of CO2 laser cutting is limited. More precisely, accounting for 70% of the total papers reviewed, the application the TM is related to Nd:YAG pulsed laser oxygen cutting, from which all are focused on solving multi-objective optimization problems. As seen from Table 1 most of the applications of the TM considers multi-objective optimization of kerf quality characteristics, kerf quality characteristics and material removal rate and kerf quality characteristics and surface roughness.

Although the TM belongs to the technique of single-objective optimization, combined with grey relational analysis (GRA), principal component analysis (PCA), weighted sum method (WSM) and fuzzy logic (FL), the TM proved successful when applied in the case of multi-objective optimization of laser cutting.

Caydaş and Hasçalik [29] applied hybrid approach of the TM and GRA to determine optimum laser cutting parameters i.e. cutting speed and laser power for CO2 laser cutting of a 10 mm thick mild steel sheet considering multi-performance characteristics such as surface roughness, kerf width, and HAZ. Chen et al. [30] presented an approach for evaluating the process parameters in CO2 laser cutting of polymethylmethacrylate (PMMA) material using the TM and GRA. They investigated and optimized laser cutting parameters such as assist gas flow rate, pulse frequency, cutting speed and focus position. Rao and Yadava [28] presented a hybrid optimization approach based on the TM and GRA with entropy measurement for determining optimum laser cutting parameters which simultaneously minimize the kerf width, kerf taper, and kerf deviation during pulsed Nd:YAG laser cutting of nickel-based superalloy superni 718. Also, Sharma and Yadava [23] presented hybrid approach comprising of the TM and RSM for modeling and hybrid approach of the TM and GRA coupled with entropy measurement methodology for multi-objective optimization of pulsed Nd:YAG laser cutting of thin aluminum alloy sheet. The results indicated that the hybrid approaches applied for modelling and optimization of the laser beam cutting process are reasonable.

Table 1. Summary of the TM applications taken along reviewed papers.

Reference	Laser system	Parameters*	OA	Assist gas	Process performance**	Workpiece material	Multi-response
Pandey and Dubey [21]	Nd:YAG	v, p, p_w, p_f	L_{27}	O_2	K_w, K_d	duralumin	yes
Sharma and Yadava [22]	Nd:YAG	v, p, p_w, p_f	L_9	O_2	K_t, R_a	aluminium alloy	yes
Dubey and Yadava [23]	Nd:YAG	v, p, p_w, p_f	L_9	O_2	K_w, MRR	high silicon-alloy steel	yes
Dubey and Yadava [24]	Nd:YAG	v, p, p_w, p_f	L_9	O_2	K_w, K_t, K_d	superni 718	yes
Dubey and Yadava [25]	Nd:YAG	v, p, p_w, p_f	L_9	O_2	K_w, K_d	8011 aluminium alloy	yes
Dubey and Yadava [26]	Nd:YAG	v, p, p_w, p_f	L_9	O_2	K_t, MRR	8011 aluminium	yes
Rao and Yadava [27]	Nd:YAG	v, p, p_w, p_f	L_{27}	O_2	K_w, K_t, K_d	superni 718	yes
Caydaş and Hasçalik [28]	CO_2	v, P	L_{16}	O_2	K_w, R_a, HAZ	St-37	yes
Chen et al. [29]	CO_2	v, p_f, f, q	L_9	compressed air	R_a, r	PMMA	yes
El Taweel et al. [30]	CO_2	v, P, p, d, TEM	L_{16}	N_2	K_w, K_t, b	Kevlar-49	no
	* v: cutting speed, p: assist gas pressure, p_w: pulse width, p_f: pulse frequency, P: laser power, f: focus position, q: assist gas flow, d: material thickness ** K_w: kerf width, K_t: kerf taper, K_d: kerf deviation, R_a: surface roughness, HAZ: heat affected zone, MRR: material removal rate, r: optical transmittance ratio, b: burr height						

The application of WSM in combination with the TM, in which weights are assigned to each performance characteristic based on the experience of the researchers, is also a popular alternative. Dubey and Yadava [24] applied WSM for simultaneous optimization of the kerf width and MRR based on second-order RSM models with assist gas pressure, pulse width, pulse frequency and cutting speed as input process parameters. Actually the authors demonstrated that hybrid the TM and RSM (TMRSM) can be applied to Nd:YAG laser cutting optimization with multiple-quality characteristics. As noted the hybrid approach gives better quality results as compared to only the TM. Dubey and Yadava [26] optimized simultaneously kerf deviation and kerf width obtained in pulsed Nd:YAG laser cutting of 8081 aluminum alloy sheet using Taguchi quality loss function. For simultaneous optimization, the normalized quality loss function was computed and weighted to obtain total normalized quality loss for each trial condition. Dubey and Yadava [27] applied the TM to find the optimal cutting parameters for multi-objective optimization of kerf taper and MRR in Nd:YAG laser pulsed cutting of a difficult to cut material (aluminum alloy). Dubey and Yadava [25] applied a combined approach based on the TM and PCA for multi-objective optimization of Nd:YAG laser cutting. Their investigation included the analysis of the laser cutting parameters on the cut quality characteristics such as kerf width, kerf deviation, and kerf taper.

More recently, Pandey and Dubey [22] presented an integrated approach based on the TM and fuzzy logic theory for optimization of multiple-responses in Nd:YAG laser cutting of duralumin sheet. The authors demonstrated the effectiveness of the method for simultaneous improvement of the kerf width and kerf deviations at top and bottom sides.

4 CONCLUSIONS

In this paper, a review of recent applications of the Taguchi method for optimization of laser cutting was presented. Following are the major observations from the literature:

- Application of the Taguchi method in laser cutting is aimed at finding a "robust" solution i.e. identification of laser cutting conditions that are insensitive to parameter variations and noise.
- In most cases, the Taguchi method has been employed for multi-objective optimization of pulsed Nd:YAG laser oxygen cutting of various materials, mainly aluminum and its alloys. Very few works are reported on usage of the Taguchi method in CO2 laser cutting for single and multi-objective optimization.
- The most of the performance characteristics considered are related to machined geometry (kerf width, taper and kerf deviation) and surface quality characteristics (surface roughness). The application of the Taguchi method for optimization of metallurgical characteristics (heat affected zone, burr inclusion) and productivity performance characteristics (material removal rate) is limited. The Taguchi based optimization of other important performance characteristics such as specific cutting speed, productivity, processing time, costs is to be considered.
- For identification of near optimal solutions in the case of multi-objective optimization, the Taguchi method has been combined with different techniques, in most cases with grey relational analysis, weighted sum method, principal component analysis and fuzzy logic.
- The Taguchi method limits the search for the optimal parameter settings only to discrete parameter values used in the experiment matrix. As a model free optimization technique, the Taguchi method does not process any further interpolation and extrapolation. To overcome this shortcoming, the Taguchi method and response surface methodology are integrated together to incorporate the advantages of both simultaneously. No literature so far shows a hybrid approach, i.e. integration of the Taguchi method and artificial neural networks for optimization of process variables and more work is required to be done in this area.
- A possibility of using a novel approach to multi-objective process optimization, based on the Taguchi method and artificial intelligence proposed by Šibalija and Majstorović [21] is a research area of interest.

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6 REFERENCES

1. Roy, R., *A primer on the Taguchi method*, Van Nostrand Reinhold, (1990).
2. Phadke, M.S., *Quality engineering using robust design*, Prentice Hall, (1989).

3. Taguchi, G., Chowdhury, S., Wu, Y., *Taguchi's quality engineering handbook*, John Wiley & Sons, (2005).
4. Madić, M., Radovanović, M., Investigation into the effect of the cutting parameters on the burr height in CO_2 laser nitrogen cutting of AISI 304 stainless steel, *Metalurgia International*, Vol.17, No.7, pp. 74-78, (2012).
5. Radovanović, M., Madić, M., Experimental investigations of CO_2 laser cut quality: a review, *Nonconventional Technologies Review*, Vol.15, No.4, pp. 35-42, (2011).
6. Rajaram N., Sheikh-Ahmad, J., Cheraghi, S.H., CO_2 laser cut quality of 4130 steel, *International Journal of Machine Tools and Manufacture*, Vol.43, No.4, pp. 351-358, (2003).
7. Stournaras, A., Stavropoulos, P., Salonitis, K., Chryssolouris, G., An investigation of quality in CO2 laser cutting of aluminum, *CIRP Journal of Manufacturing Science and Technology*, Vol.2, No.1, pp. 61-69, (2009).
8. Eltawahni, H.A., Hagino, M., Benyounis, K.Y., Inoue, T., Olabi, A.G., Effect of CO_2 laser cutting process parameters on edge quality and operating cost of AISI316L, *Optics and Laser Technology*, Vol.44, No.4, pp. 1068-1082, (2012).
9. Choudhury, I.A., Shirley, S., Laser cutting of polymeric materials: an experimental investigation, *Optics and Laser Technology*, Vol. 42, No.3, pp. 503-508, (2010).
10. Syn, C.C., Mokhtar, M., Feng, C.J., Manurung, Y.H.P., Approach to prediction of laser cutting quality by employing fuzzy expert system, *Expert Systems with Applications*, Vol. 38, No. 6, pp. 7558-7568, (2011).
11. Dhara, S.K., Kuar, A.S., Mitra, S., An artificial neural network approach on parametric optimization of laser micro-machining of die-steel, *International Journal of Advanced Manufacturing Technology*, Vol.39, No.1-2, pp. 39-46, (2008).
12. Ciurana, J., Arias, G., Özel, T., Neural network modelling and particle swarm optimization (PSO) of process parameters in pulsed laser micromachining of hardened AISI H13 steel, *Materials and Manufacturing Processes*, Vol.24, No.3, pp. 358-368, (2009).
13. Biswas, R., Kuar, A.S., Biswas S.K., Mitra, S., Artificial neural network modelling of Nd:YAG laser microdrilling on titanium nitride—alumina composite, *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Vol.224, No.3, pp. 473-482, (2010).
14. Madić, M., Radovanović, M., Comparative modeling of CO_2 laser cutting using multiple regression analysis and artificial neural network, *International Journal of Physical Sciences*, Vol.7, No.16, pp. 2422-2430, (2012).
15. Zhang, J., Chen, J., Kirby, D., Surface roughness optimization in an end-milling operation using the Taguchi design method, *Journal of Materials Processing Technology*, Vol.184, pp. 233-239, (2007).
16. Marinković, V., Madić, M., Optimization of surface roughness in turning alloy steel by using Taguchi method, *Scientific Research and Essays*, Vol.6, No.16, pp. 3473-3483, (2011).
17. Gherman, L., Slătineanu, L., Palaghia, I., Taguchi modelling of brass electroerosion by single pulse machining, *Nonconventional Technologies Review*, Vol.16, No.2, pp. 12-15, (2012).
18. Milani, A.S., El-Lahnam, C., Nemes, J.A. Different approaches in multiple-criteria optimization using the Taguchi method: a case study in a cold heading process, *Journal of Advanced Manufacturing Systems*, Vol.3, No.1, pp. 53-68, (2004).
19. Tong, L.I., Su, C.T., Wang, C.H., The optimization of multi-response problems in the Taguchi method, *International Journal of Quality and Reliability Management*, Vol.14, No.4, pp. 367-380, (1997).
20. Jeyapaul, R., Shahabudeen, P., Krishnaiah, K., Quality management research by considering multi-response problems in the Taguchi method – a review, *International Journal of Advanced Manufacturing Technology*, Vol.26, No.11-12, pp. 1331-1337, (2005).
21. Šibalija, T., Majstorović, V., An integrated approach to optimise parameter design of multi-response processes based on Taguchi method and artificial intelligence, *Journal of Intelligent Manufacturing*, doi: 10.1007/s10845-010-0451-y.
22. Pandey, A.K., Dubey, A.K., Taguchi based fuzzy logic optimization of multiple quality characteristics in laser cutting of duralumin sheet, *Optics and Lasers in Engineering*, Vol.50, No.3, pp. 328-335, (2012).
23. Sharma, A., Yadava, V., Modelling and optimization of cut quality during pulsed Nd:YAG laser cutting of thin Al-alloy sheet for straight profile, *Optics and Laser Technology*, Vol.44, No.1, pp. 159-168, (2012).
24. Dubey, A.K., Yadava, V., Multi-objective optimisation of laser beam cutting process,

Optics and Laser Technology, Vol.40, No.3, pp. 562-570, (2008).
25. Dubey, A.K., Yadava, V., Multi-objective optimization of Nd:YAG laser cutting of nickel-based superalloy sheet using orthogonal array with principal component analysis, *Optics and Lasers in Engineering*, Vol.46, No.2, pp. 124-132, (2008).
26. Dubey, A.K., Yadava, V., Optimization of kerf quality during pulsed laser cutting of aluminium alloy sheet, *Journal of Materials Processing Technology*, Vol.204, No.1-3, pp. 412-418, (2008).
27. Dubey, A.K., Yadava, V., Robust parameter design and multi-objective optimization of laser beam cutting for aluminium alloy sheet, *International Journal of Advanced Manufacturing Technology*, Vol.38, No.3-4, pp. 268-277, (2008).
28. Rao, R., Yadava, V., Multi-objective optimization of Nd:YAG laser cutting of thin superalloy sheet using grey relational analysis with entropy measurement, *Optics and Laser Technology*, Vol.41, No.8, pp. 922-930, (2009).
29. Caydaş, U., Hasçalik, A., Use of the grey relational analysis to determine optimum laser cutting parameters with multi-performance characteristics, *Optics and Laser Technology*, Vol.40, No.7, pp. 987-994, (2008).
30. Chen, M.F., Ho, Y.S., Hsiao, W.T., Wu, T.H., Tseng, S.F., Huang, K.C., Optimized laser cutting on light guide plates using grey relational analysis, *Optics and Lasers in Engineering*, Vol.49, No.2, pp. 222-228, (2011).
31. El-Taweel, T.A., Abdel-Maaboud, A.M., Azzam, B.S., Mohammad, A.E., Parametric studies on the CO_2 laser cutting of kevlar-49 composite, *International Journal of Advanced Manufacturing Technology*, Vol.40, No.9-10, pp. 907-917, (2009).