Multi Criteria Optimization of Laser Percussion Drilling Process Using Artificial Neural Network Model Combined with Genetic Algorithm

Article *in* Materials and Manufacturing Processes · January 2006

DOI: 10.1081/AMP-200060402

Majid Ghoreishi
Khaje Nasir Toosi University of Technology

Materials and Manufacturing Processes, 21: 11–18, 2006

ISSN: 1042-6914 print/1532-2475 online
DOI: 10.1081/AMP-200060402

Taylor & Francis
Taylor & Francis Group

Multi Criteria Optimization of Laser Percussion Drilling Process Using Artificial Neural Network Model Combined with Genetic Algorithm

O. B. Nakhjavani[1] and M. Ghoreishi[2]

[1]*Department of Mechanical Engineering, Iazad University, Science and Research Branch, Tehran, Iran*
[2]*Department of Mechanical Engineering, KNT University of Technology, Tehran, Iran*

This is a study of laser percussion drilling optimization by combining the neural network method with the genetic algorithm. First, optimum input parameters of the process were obtained in order to optimize every single output parameter (response) of the zprocess regardless of their effect on each other (single criterion optimization). Then, optimum input parameters were obtained in order to optimize the effect of all output parameters in a multicriteria manner. Artificial neural network (ANN) method was employed to develop an experimental model of the process according to the experimental results. Then optimum input parameters (peak power, pulse width, pulse frequency, number of pulses, assist gas pressure, and focal plane position) were specified by using the genetic algorithm (GA). The output parameters include the hole entrance diameter, circularity of hole entrance and hole exit, and hole taper. The tests were carried out on mild steel EN3 sheets, with 2.5 mm thickness. The sheets were drilled by a 400 w pulsed Nd:YAG laser emitting at 1.06 μm wave length. Oxygen was employed as the assist gas. Considering the accuracy of the optimum numerical results and the high capability of the neural network in modeling, this method is reliable and precise and confirms the qualitative results in the previous studies. As a result, one can use this method to optimally adjust input parameters of the process in multicriteria optimization mode, which indicates substitute application of the method for optimizing the laser percussion drilling process.

Keywords GA (genetic algorithm); Laser drilling; Neural network; Optimization.

Introduction

Simplification during the development of mathematical models for laser percussion drilling leads to an inability to provide acceptable results in all conditions. Yilbas [1] developed a statistical model to be able to establish a model similar to the physical model of the process. He tried laser drilling on three other materials (stainless steel, nickel, and titanium). Since singe-pulse laser was used in the experiments, the effect of the other factors such as the number of the pulses and pulse frequency, which are important factors, were not discussed and tested. Ng and Li [2] have studied the repeatability of laser percussion drilling using a flash lamp pumped Nd:YAG laser to drill holes on stainless-steel sheets. They have found that melt ejection depends on the laser pulse width and peak power. These parameters have significant effect on entrance hole geometry and repeatability.

In another article [3] the investigators have employed an Nd:YAG laser to drill holes in thick IN 718 and Ti-6AI-4V sheets. They have discussed the geometrical features and metallurgical characteristics of drilled holes. They have found that the laser parameters such as pulse frequency and pulse energy have remarkable influence on the hole geometry (hole diameter and taper angle).

Also, Ng and Li [4] have discussed the effect of laser peak power and pulse width on the repeatability of hole geometry in laser percussion drilling. They found that higher peak power and shorter pulse width results in better hole geometry repeatability. Also, they have concluded that melt ejection and spatter formation contribute to the poor repeatability of the laser percussion drilling process.

Kamalu and Byrd [5] discussed the effect of focal distance, the plane position, surface roughness of the material, and the laser energy on the laser drilling process.

French et al. [6] used an Nd:YAG laser in laser drilling and found effective factors. They discussed the main and interaction effects of the 17 proposed factors on the quality of laser drilling.

Ghoreishi et al. [7–9] employed Central Composite Design (CCD) and Response Surface Method (RSM) to analyze the effect of six input parameters on the process. They drilled mild steel and stainless steel workpiece materials by laser drilling and expressed the process parameter effects on the diameter of the hole entrance and hole exit, hole taper, and circularity of the hole entrance and hole exit. No certain numerical value was obtained in these articles [7–9] for the input and the output parameters, and also, the parameters have not been optimized.

Ghoreishi [10] in another study investigated the effect of six laser input parameters on repeatability of drilled holes in the percussion drilling process by means of experimental design technique and statistical analysis. His results indicate that smaller hole diameters are more repeatable than larger ones.

As to work carried out in genetic algorithm (GA) optimization and neural network modeling, one can point to Chaiyaratana and Zalzala [11]. They used several neural network models to correct friction. They used GA to achieve the best neural network model.

Zuperl and Cus [12] used a neural network to achieve the best cutting conditions in the turning process. In addition, Mok et al. [13] employed the neural network and the GA

Received July 13, 2004; Accepted December 2, 2004
Address Correspondence to M. Ghoreishi, Flat 6, No. 51, 3rd Shian Street, Lavizan, Tehran 16786-79118, Iran; Fax: 0098-21-733-4338; E-mail: ghoreishi@kntu.ac.ir

to determine the optimum input parameters of the injection molding system. Considering that in previous studies [7–9] on laser percussion drilling no quantitative results were obtained, in the present study, neural network has been employed to develop experimental models of process performance. Then the optimum input parameters have been quantitatively obtained by using GA in both single criterion and multicriteria manner, the details of which will be discussed in the following sections.

METHOD OF EXPERIMENT

Laser drilling experiments were carried out on mild steel EN3 sheets, 2.5 mm thickness, with an Nd:YAG laser machine with wavelength of 1.06 μm, using oxygen as the assist gas. Diameter of the laser spot was 600 μm. Through holes were drilled in all experiments and each experiment was repeated five times and an average value was obtained as each output parameter. Since the experiments were carried out in random order thus, in addition to reducing minor errors that occurred in the observations, the effects of environmental factors of the experiment were reduced. However, the output parameters of the system were not affected. A schematic figure of the laser apparatus is shown in Fig. 1. There are different methods for training neural networks, which will be discussed in the next section. Generally, the type of network developed by different methods results in different yields. However, often the Levenberg-Marquardt (L-M) method, which is the fastest method for training of the neural network, is mainly used to developed neural networks. Among the prominent features of this method is the considerable reduction of error in the hidden layer neurons of the trained networks. MATLAB software has been used for developing neural networks. Bayesian Regularization has been employed for improving the L-M method results.

TABLE 1.—Range of parameters variation.

Input parameters	Min	Max
Peak power [Kw]	3	7
Pulse time [ms]	0.6	2
Pulse frequency [Hz]	10	50
Number of pulses	2	6
Gas pressure [bar]	2	6
Focal plane position [mm]	-0.9	+0.9

The input parameters considered in this research include: peak power, pulse time, pulse frequency, number of pulses, gas pressure, and focal plane position, and the range of variation in parameters is shown in Table 1.

The four output parameters—(a) hole entrance diameter, (b) ratio of maximum to minimum Feret diameter for hole entrance (hole entrance circularity), (c) hole exit (hole exit circularity), and (d) hole taper—were selected to achieve optimum input parameter settings in both single criterion and multicriteria optimization procedure. The pictures of drilled holes and definitions of feret diameter and other responses are presented in articles [7] and [8].

Concept of the Neural Networks

The neural system actually considers an unknown structure and, by applying optimization methods, adjusts the parameters of the unknown model in order to minimize model errors. The feed-forward back-propagation neural network is an appropriate network for approximation of complex performances [14]. In this type of network, the parameters in question are actually in the form of weight functions that relate each input to a node. The node is formed by applying a stimulus function on the algebraic sum of the output values, multiplied by the related weight

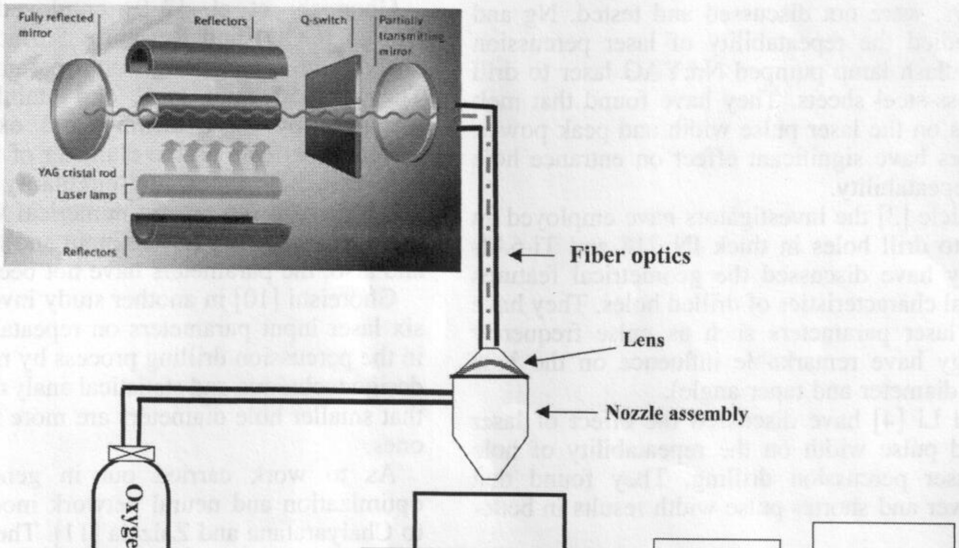

FIGURE 1.—Schematic figure of laser apparatus.

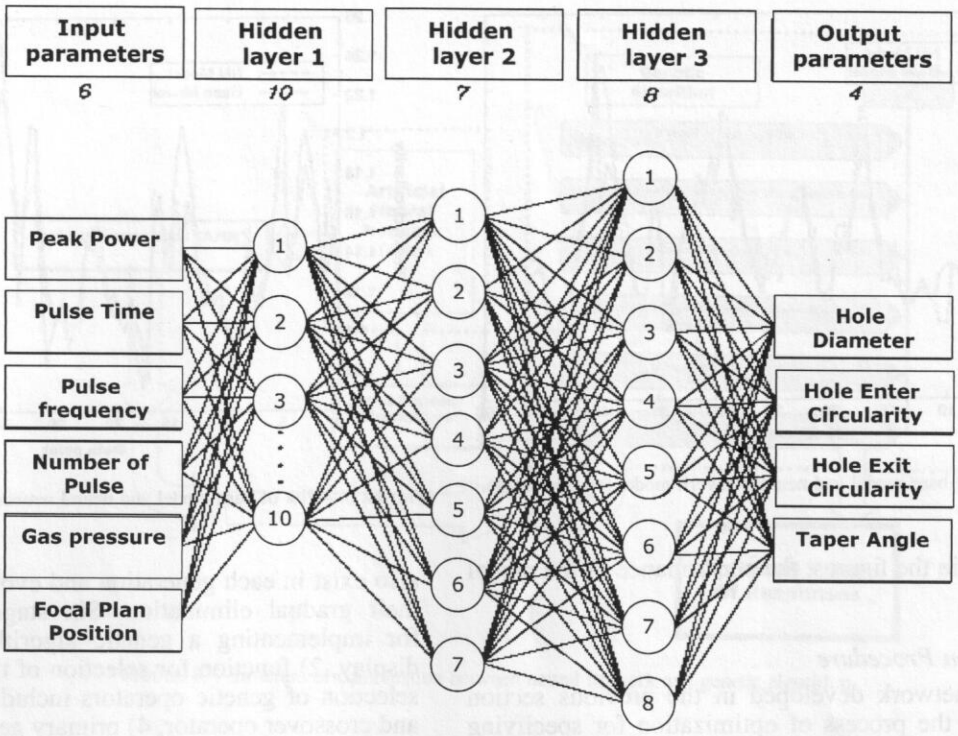

FIGURE 2.—Structure of artificial neural network (ANN).

values (Fig. 2). The common method for training of the neural network is mainly in the form of gradient methods (local optimization method), divided into four categories in the global optimization method [15].

Gradient methods include: 1) steepest descent, 2) conjugate gradient methods, 3) Newtonian methods, 4) improved Newtonian methods.

Structure of the Neural Network

After providing the necessary training of a network, it can be applied on an untrained input to achieve an appropriate output. This action is done based on the mechanism of decision making, which is an interpolation process. Accordingly, the following steps are considered in designing a neural network:

1. Determining the type of neural network.
2. Determining the proper size of the network and the type of stimulus functions.

After network designing, the network accuracy will be examined in response to inputs that are not used in the training step, so as to specify network accuracy in predicting system performance.

The neural network designed in this study is a feed-forward type with three hidden layers and an output layer. Having this model, one can obtain output process parameters related in input parameters on which no experiments have been previously carried out, in order to avoid a time-consuming, costly experiment. The main advantage of this model is its high speed in finding process responses, which, as mentioned above, are very precise compared to the experimental results. Four nodes have been considered in the output layer, including hole entrance diameter, circularity of hole entrance, circularity of hole exit, and hole taper angle (Fig. 2). The number of nodes in hidden layers have been selected, 10, seven, and eight, by trial and error (Fig. 2). Sigmoid hyperbolic type stimulus functions were chosen for the first, second, and third hidden layers, and linear type for the fourth layer (process output layer). By using the mentioned structure, the behavior of the process model (trained network) is checked and is presented in Figs. 3–7.

Figures 3–6 indicate the value of input parameters in two cases, approximated modes and the laboratory results.

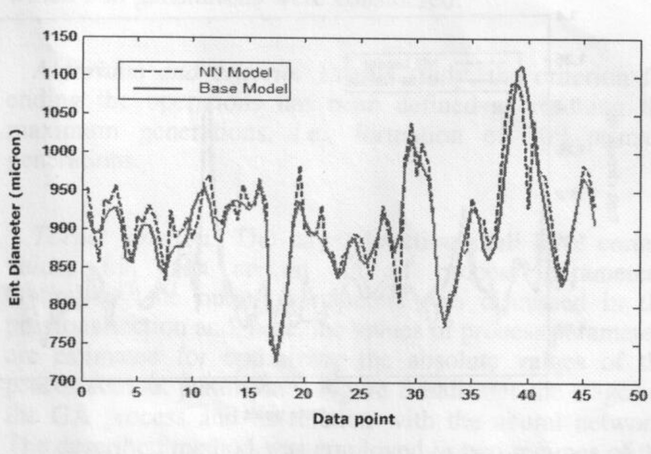

FIGURE 3.—Plot of base model and neural network model for enter diameter.

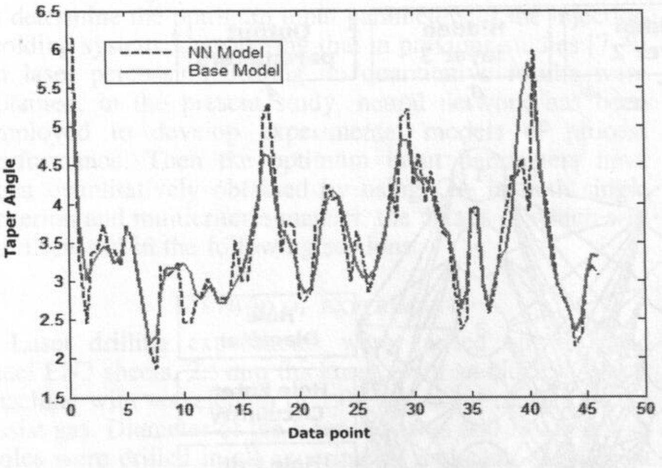

FIGURE 4.—Plot of base model and neural network model for taper angle.

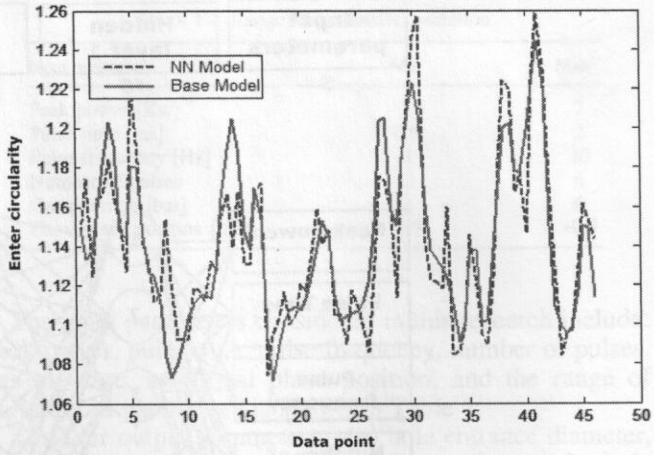

FIGURE 6.—Plot of base model and neural network model for enter circularity.

As can be seen in the figures, the performance of the model is acceptable.

GA Optimization Procedure

The neural network developed in the previous section can be used in the process of optimization for specifying the values of the target functions. Thus, in every step of the optimization process, for each set of input parameters, an output parameter is approximated and then the target function is estimated.

Nowadays, one of the powerful optimization methods employed in various cases is the GA method. Genetic algorithms have the advantage of finding a global optimum point and on the other hand does not have limitations of the gradient method, e.g., concavity, continuity, and derivability of the target function. Also, they can be applied to both linear and nonlinear systems. This method usually reaches a global answer if the parameters are precisely specified. In Fig. 8 the GA method, which has been employed in this study, is shown.

The genetic theory is based on the concept of survival of the fittest, i.e., the fittest members will survive to form the next generations. However, the less fit members may also exist in each generation and evolution will be towards their gradual elimination. Six stages shall be specified for implementing a genetic algorithms: 1) chromosome display, 2) function for selection of the next generation, 3) selection of genetic operators including mutation operator and crossover operator, 4) primary generation formation, 5) algorithm end criteria, and 6) quantifying function or target function.

In GA, each chromosome includes a string of numbers. Each process parameter used in the optimization process is coded in parts of this string and each of the parts are a string of binary digits showing the process parameter value in a binary space.

Display of chromosomes. The main discussion in display of chromosomes is determining the number of chromosomes in each generation. Five hundred chromosomes were chosen in this study.

Selection function for creation of next generations. After formation of chromosomes, the generations should be selected for creation of the new generation. This is a vital action in the genetic algorithm and depends on the

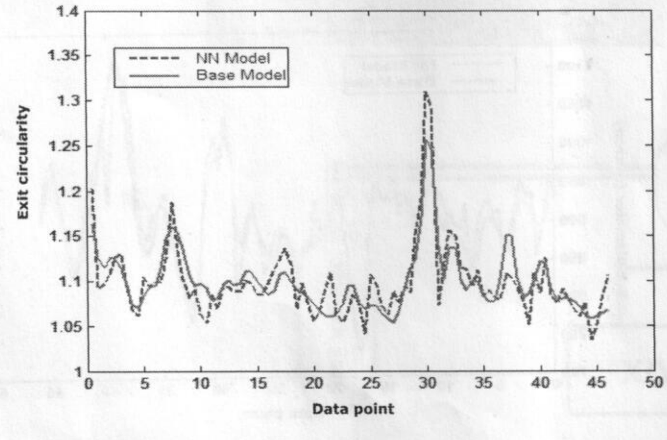

FIGURE 5.—Plot of base model and neural network model for exit circularity.

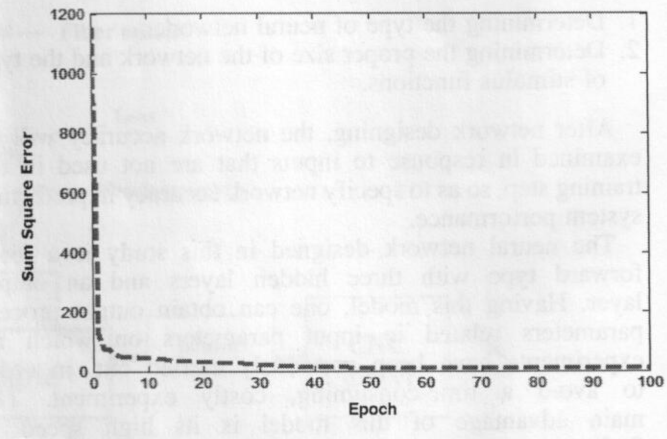

FIGURE 7.—Plot of sum square to reach an optimum model.

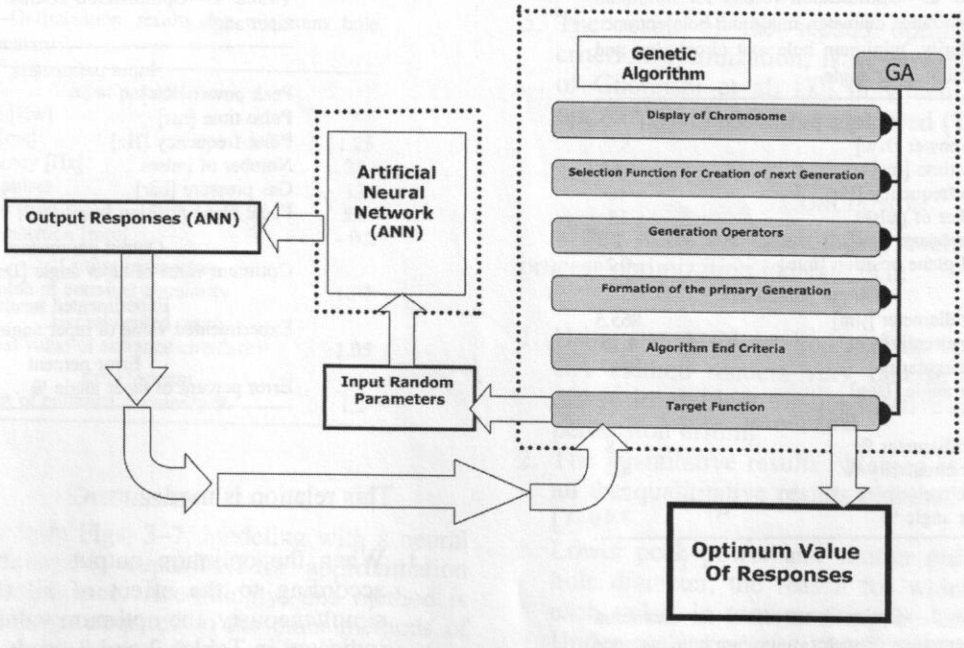

FIGURE 8.—Structure of combination between neural network and genetic algorithm.

degree of fitness of each member of a generation. There are several methods of selection. The regular method has been employed in this study. In the regular method, a random value is given to P_j (probability of selection of each member in a generation). Then a random string is formed with length N and, by adding probable values, C_i will be calculated

$$C_i = \sum_{T=1}^{1} P_j \tag{1}$$

Now a member of this generation is chosen and transferred to the next generation. If the random number has the form of:

$$C_{i-1} < U(0,1) \leqslant C_i \tag{2}$$

it applies a value on each Jth string, based on the defined fitness value. However, there are different algorithms for definition of P_j for each member of a generation. In this article, the roulette method is used, which has been presented by Professor Holland [16]. F being the degree of Fitness:

$$P[i] = \frac{F_i}{\sum_{J=1}^{\text{fopsize}} F_J} \tag{3}$$

Sealing and windowing have been employed to solve the GA maximizing action in the case of minimization.

Genetic operators. There are two principal operators:

1. Mutation (selection of a member and formation of the new member in each generation).
2. Crossover (selection of two members of a generation and formation of a new member in the next generation).

Both of these operators are based on coding circulation. The crossover method used in this study is based on the simple crossover method, which is based on changes of values of genes in a string on an intended point, which, in turn, is selected with a certain percentage of probability. The mutation method employed in this study is the regular method of mutation, which, by selecting a point with a certain degree of chance, changes the numerical value of the gene at the point from 0 to 1. Mutation actually is a type of random walking in the variable space and prohibits trapping of the system at the local optimum point. In addition, mutation makes it possible to form string patterns that may not exist in the limited primary random population.

Formation of the primary generation. After the above stages, it is time for formation of the primary generation. The Max Gen method [16] has been used in this study, for which 300 generations were considered.

Algorithm end criteria. In this study, the criterion for ending the operations has been defined as reaching the maximum generations, i.e., formation of 300 primary generations.

Target function. The target function shall have certain values for each certain set of process parameters. Optimizing the output parameters was discussed in the previous section and, here, the values of process parameters are estimated for optimizing the absolute values of the process output parameters. Figure 8 indicates the stages of the GA process and its relation with the neural network. The described method was employed in two regimes of the optimization.

TABLE 2.—Optimization results for minimum hole entrance diameter, minimum hole entrance circularity, minimum hole exit circularity, and minimum taper angle.

Input parameters	
Peak power [Kw]	5.7
Pulse time [ms]	0.62
Pulse frequency [Hz]	46
Number of pulses	15
Gas pressure [bar]	2
Focal plane position [mm]	0.2
Output parameters	
Enter diameter [μm]	865.5
Enter circularity	1.15
Exit circularity	1.17
Taper angle [Deg]	4
Error percent	
Enter diameter %	1.8
Enter circularity %	4.3
Exit circularity %	2.8
Taper angle %	3.9

TABLE 3.—Optimization results for maximum hole entrance diameter, minimum hole entrance circularity, minimum hole exit circularity, and minimum taper angle.

Input parameters	
Peak power [Kw]	5.1
Pulse time [ms]	0.74
Pulse frequency [Hz]	34
Number of pulses	12
Gas pressure [bar]	2
Focal plane position [mm]	0
Output parameters	
Enter diameter	909
Enter circularity %	1.15
Exit circularity %	1.17
Taper angle [Deg]	4.36
Error percent	
Enter diameter	1.1
Enter circularity %	4.3
Exit circularity %	2.8
Taper angle	8.2

TABLE 4.—Optimization results for minimum taper angle.

Input parameters	
Peak power [Kw]	6.97
Pulse time [ms]	1.86
Pulse frequency [Hz]	15.5
Number of pulses	6
Gas pressure [bar]	4.7
Focal plane position [mm]	−0.8
Output parameters	
Optimum value of taper angle [Deg]	1.99
Experimented result	
Experimented value of taper angle [Deg]	1.79
Error percent	
Error percent of taper angle %	10

This relation is used:

1. When the optimum output parameters are considered according to the effect of all the output parameters simultaneously, the optimum values of which have been indicated in Tables 2 and 3 (multicriteria optimization).
2. When the output parameters are considered separately regardless of the other output parameter effects. In this case, the values of output parameters are obtained, which result in optimization of only one output parameter. The optimum values are shown in Tables 4–7.

As the GA method progresses in the search for the maximum of the target function, if one of the parameters should be minimized, the parameters should be inversed.

In multicriteria optimization two optimization cases have been solved in this study. In the first case, the diameter of the hole entrance is minimized, while circularity of hole entrance, circularity of hole exit, and taper angle are minimized. The optimization results for the first case are shown in Table 2. In the second case, the diameter of the hole entrance is maximized, while circularity of hole entrance, circularity of hole exit, and taper angle are minimized. The results are shown in Table 3.

TABLE 5.—Optimization results for minimum and maximum hole entrance diameter.

	Optimum value of max enter diameter	Optimum value of min enter diameter
Input parameters		
Peak power [Kw]	5.13	5.10
Pulse time [ms]	1.22	0.63
Pulse frequency [Hz]	28.5	37
Number of pulses	9	9
Gas pressure [bar]	3.7	3.7
Focal plane position [mm]	−0.9	0.1
Output parameters		
Optimum value of enter diameter [μm]	1135.48	747.54
Experimented result		
Experimented value of enter diameter [μm]	1152.51	793.14
Error percent		
Error percent of enter diameter %	1.5	6.1

TABLE 6.—Optimization results for minimum hole entrance circularity.

Input parameters	
Peak power [Kw]	5
Pulse time [ms]	1.25
Pulse frequency [Hz]	28
Number of pulses	12
Gas pressure [bar]	5.1
Focal plane position [mm]	−0.2
Output parameters	
Optimum value of entrance circularity	1.07
Experimented result	
Experimented value of entrance circularity	1.05
Error percent	
Error percent of entrance circularity %	1.2

DISCUSSION

As can be seen from Figs. 3–7, modeling with a neural network has considerable capability for approximation of the process performance. Accordingly, this method is preferred for modeling compared to the other methods of modeling approximation such as Response Surface Method (RSM). It is known that GA is a global optimization method and the results of this algorithm are reliable. In this section, the result of the GA optimization method is compared with the results of the RSM method, which is discussed in previous articles [7, 9].

1. Reducing the pulse time and the negative focal plane position can result in reduction of the hole diameter. The results in Table 2 show this quantitatively.
2. Increase in maximum pulse power and increase in pulse time result in reduction of the taper angle. The quantitative results in Table 3 indicate this.
3. Reduction of pulse time, the negative (−) focal plane position, increase in peak power, and reduction of assist gas pressure can render minimum hole entrance circularity, which is shown by the quantitative results in Table 5.
4. Increase in pulse time, negative focal plane position, reduction of peak power, and increase in assist gas pressure can render maximum hole exit circularity, which is quantitatively shown in Table 6.

TABLE 7.—Optimization results for minimum hole exit circularity.

Input parameters	
Peak power [Kw]	4.6
Pulse time [ms]	1.31
Pulse frequency [Hz]	20
Number of pulses	13
Gas pressure [bar]	4
Focal plane position [mm]	0
Output parameters	
Optimum value of exit circularity	1.05
Experimented result	
Experimented value of exit circularity	1.06
Error percent	
Error percent of exit circularity %	1.2

5. The result of the second optimization case, single criterion optimization, is in agreement with the results of Ghoreishi et al. [7], in which the single criterion optimization has been considered (Tables 4–7).

CONCLUSION

In this study the quantitative results obtained from the process optimization indicate that:

1. Using the ANN method and its combination with the GA method renders very precise and close-to-reality results in multicriteria quantitative optimization of laser percussion drilling.
2. The quantitative results obtained in this article confirm all the qualititative results obtained in previous articles [7–9].
3. Lower peak power and shorter pulse time can reduce hole diameter, the reason for which is less energy in each pulse, in turn resulting in less material removal. Under such conditions, high pressure of the assist gas and the negative focal plane position causes reduction of the taper angle.
4. Higher peak power and longer pulse time causes reduction of taper angle. In this condition there is more energy in each pulse, which can fully guide the materials to the lower part of the hole so as to increase hole exit diameter, in turn resulting in reduction of taper angle.

Finally, the quantitative results of this study indicate that the neural network and its combination with GAs can be used for multicriteria optimization of the laser percussion drilling process, which can be employed in off-line optimum control mode.

The results of this study can be saved in a database for future studies in order to be employed in optimum application of the process for drilling holes on all materials.

REFERENCES

1. Yilbas, B.S. Parametric study to improve laser hole drilling process. J. Mat Proc. Tech. **1997**, *70* (3), 264–273.
2. Ng, G.K.L.; Li, L. Repeatability characteristics of laser percussion drilling of stainless-steel sheets. Optics and Lasers in Engineering **2003**, *39* (1), 25–33.
3. Bandyopadhyay, S.; Sundar, J.K.S.; Sundararajan, G.; Joshi, S.V. Geometrical features and metallurgical characteristics of Nd:YAG laser drilled holes in thick IN718 and Ti-6Al-4V sheets. Materials Processing Technology **2002**, *127* (1), 83–95.
4. Ng, G.K.L.; Li, L. The effect of laser peak power and pulse width on the hole geometry repeatability in laser percussion drilling. Optics and Lasers in Engineering **2001**, *33* (6), 393–402.
5. Kamalu, J.; Byrd, J.P. Statistical design of laser drilling experiments. In Proc. ICALEO 98, Sect. B, 1998, 282–287.
6. French, P.W.; Hand, D.P.; Peters, C.; Shannon, G.J.; Byrd, P.; Watkins, K.; Steen, W.M. Investigation of Nd:YAG laser percussion drilling process using factorial experimental designs. In Proc. ICALEO 99, Sect. C, 1999, C51–C60.

7. Ghoreishi, M.; Low, D.K.Y.; Li, L. Statistical modelling of laser percussion drilling for hole taper and circularity control. ImechE Part B: J. Eng. Manufact. **2002**, *216* (13), 307–319.
8. Ghoreishi, M.; Low, D.K.Y.; Li, L. Comparative statistical analysis of hole taper and circularity in laser percussion drilling. International Journal of Machine Tools and Manufacture **2002**, *42*.
9. Li, L.; Low, D.K.Y.; Ghoreshi, M. Hole taper characterisation and control in laser percussion drilling. Annals of the CIRP **2002**, *51* (1), 179–184.
10. Ghoreishi, M. Statistical analysis of repeatability in laser percussion drilling. Int. J. Advanced Manufacturing Technology (in press).
11. Chaiyaratana, N.; Zalzala, A.M.S. Hybridisation of neural networks and a genetic algorithm for friction compensation. Congress on Evolutionary Computation **2000**, *1* (2), 22–29.
12. Zuperl, U.; Cus, F. Optimization of cutting conditions during cutting by using neural networks. Robotics and Computer Integrated Manufacturing **2003**, 189–199.
13. Mok, S.L.; Kwong, C.K.; Lau, W.S. A hybrid neural network and genetic algorithm approach to the determination of initial process parameters for injection molding. Advance Manufacturing Technology **2001**, *18* (6), 404–409.
14. Haykin, S. *Neural Networks: A Comprehensive Foundation*, 2nd Ed.; Prentice Hall: London, 1998.
15. Neural Network Toolbox 3.0 for use with MATLAB, Math work, 1998.
16. Houck, C.R.; Joines, J.A.; Kay, M.G. *A Genetic Algorithm for Function Optimization*; North Carolina State University, USA, 2000.