Statistical and Numerical Approaches for Modelling and Optimising Laser Micromachining Process-Review

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ABSTRACT

This chapter presents the modelling and optimization techniques commonly used in engineering applications especially in Laser Micromachining process. Design of Experiment DOE (Response Surface Method and Taguchi), Artificial Neural Network (ANN), Genetic Algorithm (GA), and Particle swarm optimization (PSO) and mixed techniques are explained briefly. Furthermore, a review of laser micromachining processes parameters optimization was studied. Recent researches which used different approaches for modelling and optimization was presented.

Keywords: Laser micromachining; Modelling; Optimization;

1.1 Introduction

Modelling and optimization techniques which are a set of mathematical and statistical techniques are useful for modelling and predicting the desired responses in different processes. Also selecting the process input parameters in order to obtain a high quality process is desirable. Conducting experiments based on a trial-and-error method is time-consuming and does not consider the interaction effects of the parameters, and causes a great deal of errors. In laser materials processing especially laser machining as an old methods of laser processes, modelling and optimization methods have widely used. Therefore the aim of this chapter is to present applied techniques for modelling and optimization in the laser machining process.

In this chapter book Design of Experiment DOE (Response Surface Method and Taguchi), Artificial Neural Network (ANN), Genetic Algorithm (GA), and Particle swarm optimization (PSO) and mixed techniques (ANN+GA and FEM+DOE+GA+ANN) are explained briefly. At the last section, a review of laser micromachining processes parameters optimization is surveyed. Recent researches which used different approaches for modelling and optimization in advanced engineering machining processes is presented.

1.2 Design of Experiment

Experimental design or Design of Experiments (DOE) is the design of any information-gathering experiments where variation is present in the system under investigation. DOE is an organised methodology for examination of a system or process. A series of organised tests are designed in which systematic changes are made to the input variables of a process or system. The effects of these changes on a predetermined output are then evaluated.

1.2.1 Introduction

Typically, experiments are carried out in the industry to enhance the understanding and knowledge of different manufacturing processes with the objective of manufacturing high-quality products. To ensure a continuous progress in process quality, it is important to be aware of the process behaviour, the extent of variability, and its influence on the process outputs. Usually, experiments are often carried out, in the engineering arena, to explore, estimate, or confirm. Exploration denotes the understanding the data from the process. Estimation denotes the specification of the effect of the process variables on the output characteristics. Confirmation involves verifying the predicted results obtained from the experiment [1].

DOE is an organised methodology for examination of a system or process. A series of organised tests are designed in which systematic changes are made to the input variables of a process or system. The effects of these changes on a predetermined output are then evaluated. DOE is significant as a formal way of maximising information acquired while minimising resources needed. Since it allows a conclusion on the significance to the output of input variables acting in combination with one another, as well as input variables acting alone, DOE offers more conclusions than 'one change at a time' experimental approaches.

One of the conventional and regular approaches utilised by manufacturing engineers in industry is one-variable-at-a-time (OVAT), where the engineer varies one variable at a time keeping all other variables involved in the experiment fixed. OVAT testing always holds the chance that the person who is conducting the experiments may discover that one input variable will have a significant effect on the response (output) while failing to find that changing another variable may modify the effect of the first (i.e. where there is dependency or interaction). This OVAT approach needs considerable resources to acquire a limited amount of information about the process. Usually, OVAT experiments are time-consuming, unlikely to yield the optimal condition and do not examine the interaction between the process variables [1].

Methods that have statistical foundations can replace OVAT methodology. The design of Experiment (DOE) methodology plays a major role in planning, conducting, analysing, and interpreting data from experiments. If a certain quality feature of a product (the output or response) is being affected by several variables, the best tactic is to design an experiment in order to attain valid, reliable, and sound conclusions in an economical, effective, and efficient manner. It is essential to know that some factors may have strong effects on the output, others may have modest effects, and some have no effects at all. Consequently, the objective of a well-designed experiment is to determine which set of factors in the process affects the process performance most, and then the best levels for these factors to reach the sought after quality level can be determined [2].

DOE designs and arranges for all possible dependencies in the first place, and then proposes exactly what data are required to assess them i.e. whether input variables change the response when combined, on their own, or not at all [1]. DOE can be used to answer questions like "what is the key contributing factor to a problem?", "how well does the system/process carry out in the existence of noise?", "what is the best pattern of factor values to minimise variation in a response?" etc. In general, these questions are given tags as specific kinds of studies. For the type of problem-solving questions mentioned above, DOE can be used to find the answer. Taking into account, DOE requires different experimental factors to answer a different question.

The order of tasks to using this tool begins with identifying the input variables and the response (output) that is to be evaluated. For each input variable, a number of levels are determined that represent the range for which the effect of that variable needs to be known. An experimental design is developed which tells the person who is conducting the experiments where to set each test parameter for each run of the experiment. The response is then quantified for each run. The technique of analysis is to look for variances between response (output) readings for different groups of the input changes. These variances are then accredited to single effect (the input variables acting alone) or an interaction (in combination with another input variable) [3].

Since a variety of backgrounds (e.g. design, manufacturing, statistics etc.) should be involved when identifying factors and levels, DOE is team oriented. Moreover, the team should have a full understanding of the difference between control and noise factors because this tool is used to answer particular questions. From each performed experiment, it is crucial to obtain the maximum amount of information. Therefore, a full matrix is needed which contains all possible combinations of factors and levels. Well-designed experiments can produce significantly more information and often require fewer runs than random or unplanned experiments. Furthermore, a well-designed experiment will ensure that the assessment of the effects that had been identified as important. For instance, if there is an interaction between two input variables, both variables should be considered in the design rather than doing a “one factor at a time' experiment. An interaction occurs when the effect of one input variable is affected by the level of another input variable [1, 3, 4].

Sir R. Fisher introduced DOE in the early 1920s to determine the effect of various fertilisers on a range of land plots [1]. Since then, DOE has been employed in many domains such as engineering, physics, chemistry, etc. The use of DOE has grown rapidly in the last two decades and has been adapted for many industrial processes such as chemical mixing, welding, and micromachining to find out the optimal conditions. Responses surface methodology (RSM) is the most known type of DOE design; the concept of RSM was introduced in the early 50's by Box and Wilson [5, 6].

Thoughtful planning helps to avoid problems that can occur during the accomplishment of the experimental design. For example, personnel, tools availability, funding, and the mechanical characteristics of the system may affect the ability to complete the experiment. The preparation needed before starting experimentation relies on the nature of the problem. Some of the steps that may be essential are problem definition, objective definition, developing an experimental plan, and finally, making sure the process and measurement systems are in control.

In terms of problem definition, picking a good problem statement helps make sure that the correct variables are considered. This step is used to identify the questions that need to be answered. While in terms of objective definition, a well-defined objective will guarantee that the experiment answers the right questions and produces practical, usable information. This step is used to define the goals of the experiment.

Then the experimental plan should be developed in such a way, it will provide meaningful information. At this step, it is essential to make sure that the relevant background information has been studied, like theoretical principles, and knowledge obtained through observation or previous experimentation. For instance, correct identification of which factors or process conditions affect process performance and contribute to process variability is necessary. Alternatively, if the process is already established and the influential factors have been identified, it may be required to determine the optimal process conditions.

Ideally, both the process and the measurements should be in statistical control as measured by a functioning statistical process control (SPC) system. This will guarantee that the process and measurement systems are in control. Even if it does not have the process completely in control, it must be able to reproduce process settings [7]. In addition, it is necessary to determine the variability in the measurement system.

In many process development and manufacturing applications, potentially influential variables are many. Screening reduces the number of variables by identifying the significant variables that affect product quality. This reduction allows process improvement efforts to be focused on the key variables. Screening may also propose the “optimal” or best settings for these factors, and indicate whether curvature exists in the responses. Then, it can use optimisation methods to determine the best settings and define the nature of the curvature. General full factorial designs (designs with more than two levels) may be particularly useful for screening experiments.

1.2.2 Response Surface Methodology (RSM)

RSM is a group of statistical and mathematical techniques that are useful for modelling and predicting the output of interest influenced by some input variables with the objective of optimising this output [8-11]. RSM also describes the relationships among one or more measured outputs and the vital controllable input factors [12]. If all independent variables are measurable and can be repeated with negligible error, the response surface (output surface) can be expressed by Equation **Error! Reference source not found.**.

$$y = f(x_1, x_2, x_3, \dots, x_k) \quad 1$$

$$y = a_0 + \sum a_i x_i + \sum a_{ij} x_i x_j + \sum a_{ii} x_{ii}^2 + \varepsilon \quad 2$$

where k is the number of independent variables.

Usually, engineers search for the conditions that would optimise the process of interest. It means that they want to find the values of the process input parameters at which the responses reach their favourable outcome or "optimum". The optimum could be either a minimum or a maximum of a particular outcome in terms of the process input parameters. RSM is one of the optimisation techniques currently in widespread usage to describe the performance of the micromachining process and find the optimum of the responses of interest. Therefore, it is essential to find an appropriate approximation for the true functional relationship between the independent variables and the response surface, in order to optimise the response "y". Generally, RSM uses a second order polynomial mathematical equation similar to Equation **Error! Reference source not found.**. A description of the general RSM procedure can be found in **Error! Reference source not found.** respectively.

1.2.3 Taguchi

Recent industrial applications have been particularly associated with the name of the Japanese engineer, G. Taguchi. The Taguchi method optimizes design parameters to minimize variation before optimizing design to hit mean target values for output parameters. The Taguchi method uses special orthogonal arrays to study all the design factors with minimum of experiments. One of the novel design aspects of Taguchi's contributions is the emphasis on the study and control of product variability, especially in contexts where achievement of a target mean value of some feature is relatively easy and where high quality hinges on low variability. Factors which cannot be controlled in a production environment but which can be controlled in a research setting are deliberately varied as so-called noise factors, often in split-unit designs. Another is the systematic use of orthogonal arrays to investigate main effects and sometimes two factor interactions. An example of Taguchi orthogonal array is denoted by L18 (36) to indicate eighteen runs, and six factors with three levels each. It should be noted that the full factorial of six factors with three levels will be 729 runs which is decreased to 18 runs by using Taguchi method. Signal to noise (S/N) ratio is defined in the Taguchi approach to determine optimal levels of each parameter and also analyzing the parameter variation. Two equations are presented which are known as standard ratio and are more applicable. In these equations Yi is the response value and n is the number of repeat observations. To optimize the system when the response is maximum, "Larger is better" state is considered that can be calculated by Equation (3), SN_L. To optimize the system when the response is minimum, "Smaller is better" state is considered that can be calculated by Equation (4), SN_S.

$$SN_L = -10 \log[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{{y_i}^2}] \quad 3$$

$$SN_S = -10 \log[\frac{1}{n}\sum_{i=1}^{n}{y_i}^2] \quad 4$$

1.3 Artificial Neural Network (ANN)

Artificial Neural Network is a type of Artificial Intelligence (AI) originally designed to mimic the massively parallel operations of the human brain and aspects of how we believe the brain works. Neural network nodal functions can be evaluated simultaneously, thereby gaining enormous increases in processing speed [13].

A neural network can be considered as a black box that is able to predict an output pattern when it recognises a given input pattern. Once trained, the neural network is able to recognise similarities when presented with a new input pattern, resulting in a predicted output pattern.

In the fields of artificial intelligence, Artificial Neural Network (ANN) is a mathematical model that simulates the biological neural networks. A neural network is an assembly of interconnected processing elements, known as nodes or artificial neurones.

1.3.1 Introduction

Frequently, ANN is used to model complex relationships between inputs and outputs. The ability of an ANN to make predictions is based on the inter-neurons connection strengths, known as “weights”, which are acquired through a set of training data by a process of adaptation called “supervised learning” [14].

The ANN has similar principle to that of a biological neural network where each node represents a biological neurone. Figure displays a biological and artificial neurone. Furthermore, this figure shows the obvious resemblance between the two types of neurone.

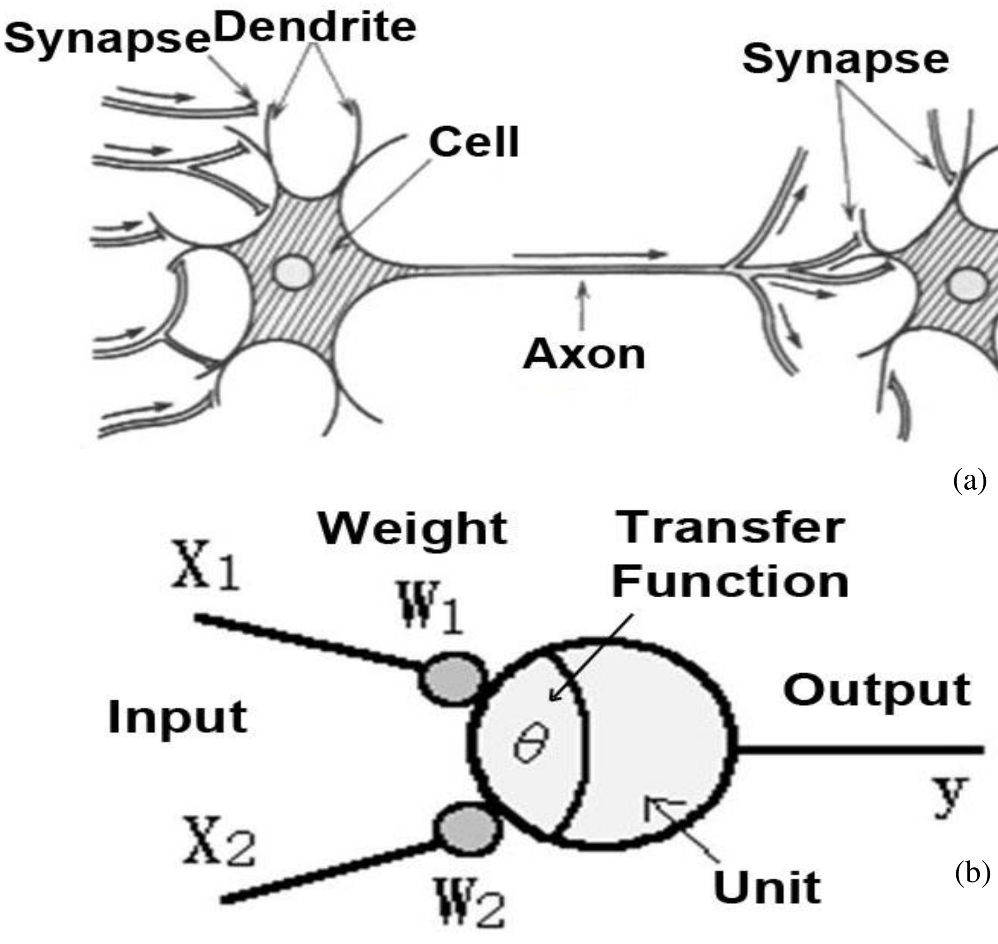

Figure 1: (a) Biological neurone and (b) artificial neurone.

There is a weight associated with the incoming synapse of a biological neurone. The weight of each synapse, times its input, is summed for all incoming synapses and the neurone then fires, sending a signal (electrical activity) to another neurone in the network. In ANN, almost the same principle applies. Each node in the ANN has a set of inputs (analogous to the synapses in a biological neurone). Each input connection has a quantity (the connection strength or weight) associated with it. Bias is a constant input with a certain weight. Each node has a summing function for computing the weighted sum of the inputs. Moreover, it has an "activation function" (or transfer function) for limiting the amplitude of the neurone output [15]. Figure shows a mathematical representation of a single neurone.

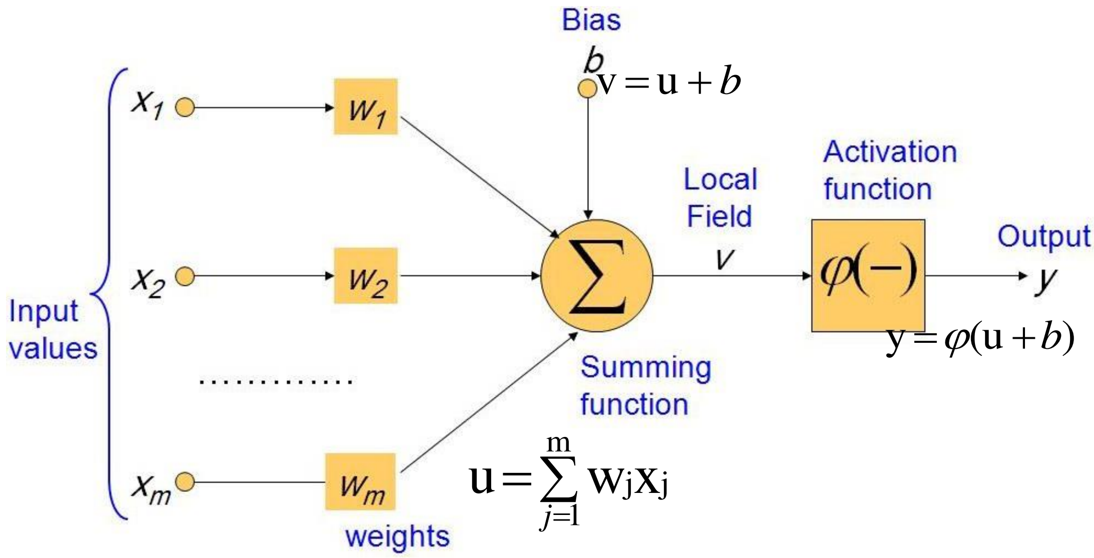

Figure 2: A single neurone may be represented mathematically.

The mathematical output value of a single neurone may be calculated according to formulas from Equation **Error! Reference source not found.** to Equation **Error! Reference source not found.**.

$$u = \sum_{j=1}^{m} w_j x_j \quad (5)$$

$$V = u + b \quad (6)$$

$$y = \varphi(v) \quad (7)$$

where x is a neurone with m inputs and one output $y(x)$, and w_j are weights determining how much each input should be weighted. φ is an activation function that weights how influential the output (if any) should be from the neurone, based on the sum of the input.

In order to introduce non-linearity to the neural network, the proper transfer or activation function should be selected. Activation functions vary from simple threshold functions to sigmoid or hyperbolic tangent functions. It is essential to introduce non-linearity to the ANN, as this is what provides the computational power to the network. Without this non-linearity, the network turns into a basic matrix multiplication operation.

The sigmoid transfer function is a mathematical function having an "S" shape (sigmoid curve). It takes the input, which may have any value between minus and plus infinity, and provides an output in the range 0 to 1. The sigmoid function may be written as Equation 8.

$$f(x) = \frac{1}{1 + e^{-t}} \qquad 8$$

This transfer function is commonly used in back-propagation networks of the type used in this study due to its differentiability [16]. The learning rate parameter, which is the training parameter that controls the size of weight and bias changes during learning, can be set during simulation to control the magnitude of weight and bias updates. The selection of this value significantly affects the training time of the ANN. The “momentum” technique is often utilised to decrease the likeliness for a back-propagation network to be stuck in local optima [15].

1.3.2 ANN Structure

The nodes in ANN are arranged in layers. Each of the nodes in a given layer is connected to nodes in another layer. Typically, there are three types of layers to an ANN: an input layer, one or more hidden layers, and an output layer. Figure shows typical three-layered feed forward neural network architecture, where there are three inputs, four neurones in the hidden layer, and two outputs.

The input layer is where the data vector is fed into the network. This feeds into the hidden layer, which in turn feeds into the output layer. The processing of the network occurs in the nodes of the hidden layer and the output layer. There are numerous ANN structures; however, the feed forward and recurrent structures are the most frequent. Since neural networks of feed forward structure and back-propagation algorithm offer better prediction capability [17, 18], this specific type of ANN was employed in this work.

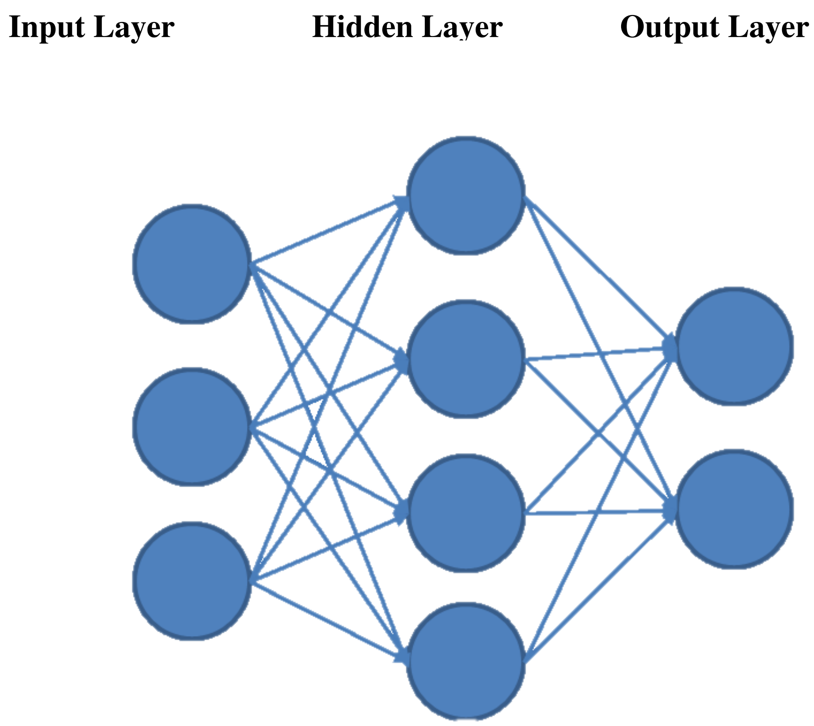

Figure 3: Typical three-layered feed forward neural network architecture.

Feed-forward networks

Signals, in the feed-forward structure, travel one-way (forward), from inputs to output(s) without any backtracking along the way. Figure shows a typical feed-forward neural network. In the feed-forward network, data are uniformly processed in one direction from the input towards the output layer. Therefore, all links are unidirectional, and no cycles are present in ANNs of the feed-forward structure.

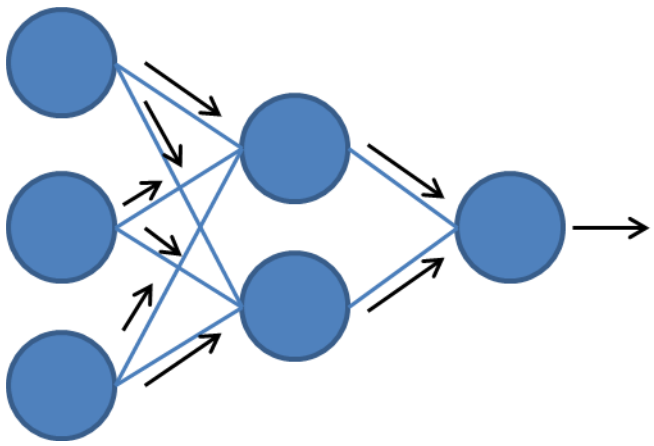

Figure 4: A representation of a feed-forward neural network.

Multi-layered perceptron is an ANN feed forward structure with one or more hidden layers between the input and output nodes. The advantage of multilayer perceptrons is that the number of nodes in the hidden layer can be varied to adapt to the complexity of the relationships between input and output variables [15]. One of the experimental aims of this work was to determine the number of hidden layers and the size (number of neurones) of these hidden layers that produce the best predictive performance.

Recurrent Neural Networks (RNNs)

Signals, in the recurrent structure, can travel in all directions with loops, allowing its output to be used in previously used "neurones". Therefore, these are models with the bi-directional data flow. While feed-forward network propagates data from input to output, RNNs propagate data from "downstream" processing units to earlier units. Thus RNNs, have feedback connections between units of different layers or loop type self-connections [19, 20]. This implies that the output of the network not only depends on the external inputs but also on the state of the network in the previous time step as is shown in Figure .

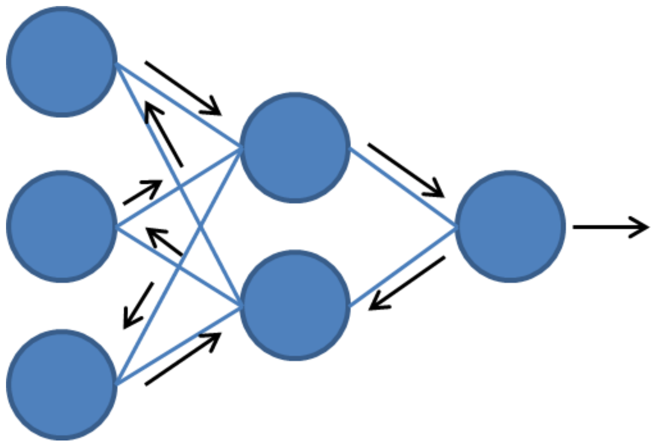

Figure 5: A representation of a recurrent neural network.

1.3.3 Learning Paradigms

Although it is not possible to model a human brain exactly with its enormous complexity, an ANN can be used to solve problems of considerable complexity. Learning can be achieved by proper ANN training. There are several ANN learning methods. The supervised and the unsupervised learning methods are the most common learning methods for ANN. However, the supervised ANN learning method was adopted for this work.

Supervised Learning

This method is the most common ANN learning method. In this learning method, the output of a neural network is compared to the actual output. Weights, which initially are set to random, are adjusted by the network so that the next iteration will yield a closer match to the actual output. The learning method attempts to minimise the current errors of all neurones. This global error reduction is made over time by continuously modifying the weights until acceptable network accuracy is reached. In this learning method, the ANN must be trained before it becomes useful. Training consists of presenting input and output data (training set) to the network. Supervised learning is an ideal process for prediction of an input/output functional relationship.

Unsupervised Learning

Unsupervised learning differs from supervised learning in describing data rather than predicting. This learning method, sometimes called self-supervised learning, is not common and limited to networks known as self-organizing maps. In this learning method, the network observers their performance internally and no external effects are used to adjust its weights. The network looks for uniformities (trends) in the input signals and makes adaptations according to the function of the network. Even without being told whether it is right or wrong, the network still must have some information about how to organise itself. This information is built into the network topology and learning rules [15, 21]. Unsupervised learning is an ideal process for clustering similar data.

1.3.4 The Back-Propagation algorithm

Back-propagation algorithm is the most common supervised learning algorithm. The concept of this algorithm is to adjust the weights minimising the error between the actual output and the predicted output of the ANN using a function based on delta rule. It involves working backwards from the output layer to adjust the weights accordingly and reduce the average error across all layers. This process is repeated until the output error is minimised. The basic back-propagation algorithm adjusts the weights in the steepest descent direction [22-24].

Using this algorithm, the network training consists of three stages: (a) feed-forward of the input training pattern; (b) calculation and back-propagation of the associated error; and (c) the adjustment of the weights. By starting from the output layer, backwards pass propagates the error. This process continues until the minimum error is reached. In weight update phase, input activation level and output delta are multiplied to get the gradient weight. Then weights are put in the reverse direction of the gradient by subtracting the ratio of it from the weight [25]. Since data normalisation minimises the chances of convergence to a local minimum on the error surface, convergence is more readily achieved through normalisation of the input and output data [26].

1.3.5 ANN Training, Validation and Testing

At the start of the training phase, the weights and the biases in the neural network are initialised to small random values between -0.1 and +0.1. The training process involves feeding the ANN known inputs and outputs, which gradually modify the connection weights. The back-propagation learning algorithm is implemented to modify the values of the weights. The weights eventually converge to values, which allow them to be used in predicting an unknown output.

In order to use a neural network as a predictive tool, the available data is divided into three subsets, for training, validation and testing. Overtraining (or over fitting) begins when the network starts to memorise and this render it unable to generalise due to being overtrained. To avoid over training, an early stopping mechanism should be incorporated into the ANN. As the weights and biases of the network are updated continuously to minimise the MSE (Mean Squared Error) of the training data, the error of the validation data is also calculated, and if the MSE of the validation data starts to increase, training is stopped. This is known as "cross-validation". After the training phase, the ANN is used to simulate the output of a set of test data. If the ANN returns values of the output for the test data within an acceptable margin, then the ANN can be said to be successfully trained, and may be used as a predictive tool [16, 27, 28].

1.4 Genetic Algorithm (GA)

Genetic algorithm was developed based on the features of natural biological evolution and Darwinian struggle for survival. GAs are search algorithms to mimic the principles of biological evolution and also known as stochastic sampling methods. They can be used to solve difficult problems in terms of objective functions that possess 'bad' properties, such as multi-modal, discontinuous, non-differentiable, etc. These algorithms maintain and manipulate a population of solutions and implement their search for better solutions based on 'survival of the fittest' strategy. GAs solve linear and non-linear problems by exploring all regions of the solution space and exploiting promising areas [29].

1.4.1 Introduction

The genetic algorithm is a method for solving optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions [30]. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

The basic steps of a genetic algorithm are expressed as follows [31]:

(1) Problem definition.
(2) Initialization of the population: A population is a set of vectors which called a chromosome. Each chromosome contains optimizing parameters.
(3) Calculation of fitness: The fitness of each chromosome in the generation is assessed by determining its fitness function.
(4) Selection: At this step, reproduction occurs, and this means which chromosomes are chosen according to their fitness and use as parents
(5) Crossover: A new chromosome is generated from the parents by combining these two halves of the genetic code.
The new chromosome gains its characteristics from both parents.
(6) Mutation: A new chromosome is generated by a small change in the randomly selected bits of old genes.
(7) Go to step 4, if the solution is not suitable
Therefore, GA is an aggressive search technique that quickly converges to find the optimal solution in a large solution domain.

1.4.2 Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) is one of the population-based stochastic optimization technique inspired by social behaviour of bird flocking developed by Kennedy and Eberhart [29]. PSO is a parallel evolutionary computation technique and shares many similarities with other evolutionary techniques such as Genetic Algorithms (GA). A population of random individuals is initially generated and these individuals probe the search space during their evolution to identify the optimal solution. Compared to GA, PSO does not employed evolution operators such as crossover and mutation and does not need information about the objective function gradient [31].

Particle swarm optimization can be used across a wide range of applications. Areas where PSOs have shown particular promise include multimodal problems and problems for which there is no specialized method available or all specialized methods give unsatisfactory results.

In PSO, the individuals, called particles, are collected into a swarm and fly through the problem space by following the optima particles. Each individual has a memory, remembering the best position of the search space it has ever visited. In particular, particle remembers the best position among those it has visited, referred to as pbest, and the best position by its neighbours [32].

Suppose that the search space is n-dimensional, and then the particle i of the swarm can be represented by an n-dimensional vector $X_i = (x_{i1}, x_{i2}, \dots, x_{i3})$. The velocity of this particle can be represented by another n-dimensional vector $V_i = (v_{i1}, v_{i2}, \dots, v_{in})$. The fitness of each particle can be evaluated according to the objective function of optimization problem. The best previously visited position of the particle i is noted as its individual best position $P_i = (p_{i1}, p_{i2}, \dots, p_{in})$. The position of the best individual of the whole swarm is noted as the global best position$G = (g_{i1}, g_{i2}, \dots, g_{in})$. At each step, the velocity of particle and its new position will be assigned according to the following two equations:

$$V_i = \omega * V_i + c1 * r_1 * (P_i - X_i) + c2 * r_2 * (G - X_i) \qquad (9)$$

$$X_i = X_i + V_i \qquad (10)$$

where, x is called the inertia weight that controls the impact of previous velocity of particle on its current one. $r_1;r_2$ are independently uniformly distributed random variables with range (0,1). $c_1;c_2$ are positive constant parameters called acceleration coefficients which control the maximum step size.

In PSO, Eq. (9) is used to calculate the new velocity according to its previous velocity and to the distance of its current position from both its own best historical position and the best position of the entire population or its neighbourhood. Generally, the value of each component in V can be clamped to the range ($-v_{max}$;v_{max}) to control excessive roaming of particles outside the search space. Then the particle flies toward a new position according Eq. (10). This process is repeated until a user-defined stopping criterion is reached [33]. The PSO algorithm includes some tuning parameters that greatly influence the algorithm performance, often stated as the exploration–exploitation tradeoff: Exploration is the ability to test various regions in the problem space in order to locate a good optimum, hopefully the global one. Exploitation is the ability to concentrate the search around a promising candidate solution in order to locate the optimum precisely. The user can thus take well-informed decisions according to the desired exploration–exploitation tradeoff.

1.5 Mixed techniques

Mathematical function approximators and evolutionary computation techniques are able to be combined to solve complicated optimization problems in order to give a functional assessment of the process characteristics for forecasting and decision making.

ANN can be mathematically shown to be universal function approximators. This means that they can automatically approximate whatever functional form best characterizes the data. While this property is of little value if the functional form is simple (e.g. linear), it allows ANN to extract more signal from complex underlying functional forms. ANN can also partially transform the input data automatically [34].

Particle swarm optimization is one of evolutionary computation techniques that simulates social behaviours such as bird flocking or fish schooling. The principle of this technique is based on the social interaction of birds in the group which thinking is not only personal but also social to search randomly for food in the area. Each bird is a single solution, and each solution can be illustrated as a particle in the swarm. Each particle moves in the search space to look for the most favourable solutions. Therefore, each particle is specified by its position and velocity in the search space which updates them based on its personal and its neighbour experiences [35].

Genetic algorithms (GAs) are also randomized search and optimization techniques guided by the principles of evolution and natural genetics, having a large amount of implicit parallelism. GAs perform search in complex, large and multimodal landscapes, and provide near-optimal solutions for objective or fitness function of an optimization problem.

1.5.1 Introduction

Approximation ability of modelling tools such as ANN and the robust evolutionary searching performance of optimizing algorithms like GA or PSO make it possible to mix these techniques to be more effective in solving combinatorial optimization problems. It also has the primary advantage of being used for optimization of processes without explicitly knowing the forms of objective functions. The application of this strategy is recently finding increased applications in many different scientific and engineering disciplines owing to its accuracy in prediction/optimization and flexibility.

The mixed optimization method can be a systematic approach using Computer Aided Engineering (CAE), applied statistical methods such as Design of Experiments (DOE), modelling tools like Neural Network (NN) and also optimization algorithm namely Genetic Algorithm (GA) [36-38].

Numerical Analysis of engineering phenomena should be used to gain a comprehensive understanding of the engineering phenomena. CAE software like Abaqus or ANSIS utilize Finite Element Method (FEM) to carry out the Numerical Analysis.

DOE is an approach to evaluating relationships between input parameters and response variables. DOE involves determining the significant input variables influence on response variables.

ANN has shown remarkable performance when have been used for modelling complex linear and nonlinear relationships. Using ANN model with GA is a promising natural computation technique for optimization because ANN has become a practical method for predictive capability to very complex non-linear systems. One of the benefits of applying DOE before modelling with ANN is possibility of using data acquired from DOE experiments to train ANN. GA, is one of the evolutionary algorithms to solve optimization problems. Therefore, hybrid system of Computer Aided Engineering (CAE), modelling tools like Neural Network (NN) and optimization algorithms namely Genetic Algorithm (GA) is a scientific approach to solve complicated problems [39, 40].

The optimization approach includes the following steps:

1) Determine the optimization objectives.

2) Identify the significant input variables using DOE.

3) Modelling by ANN

4) Optimization by GA or PSO

Figure 6 shows the flowchart of a hybrid optimization algorithm using Finite Element, Design of Experiment (DOE) and (GA-ANN). Figure 7 presents the flowchart of genetic algorithm hybrid with artificial neural network (GA-ANN).

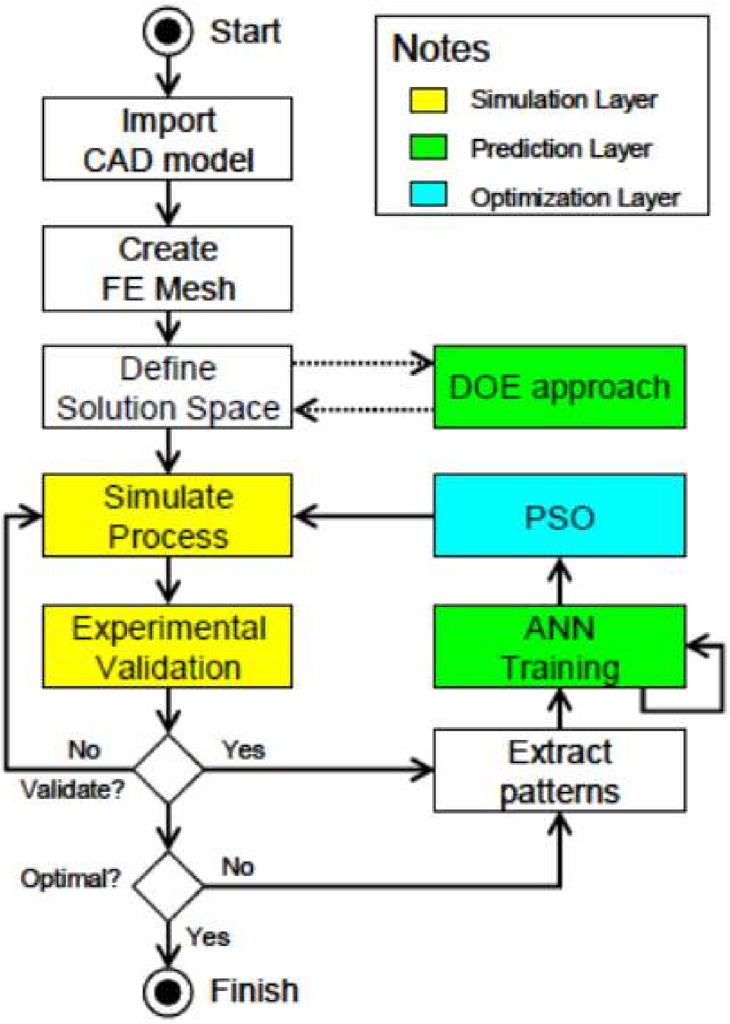

Figure 6: Flowchart of a hybrid optimization algorithm (FEM, DOE, GA and ANN)

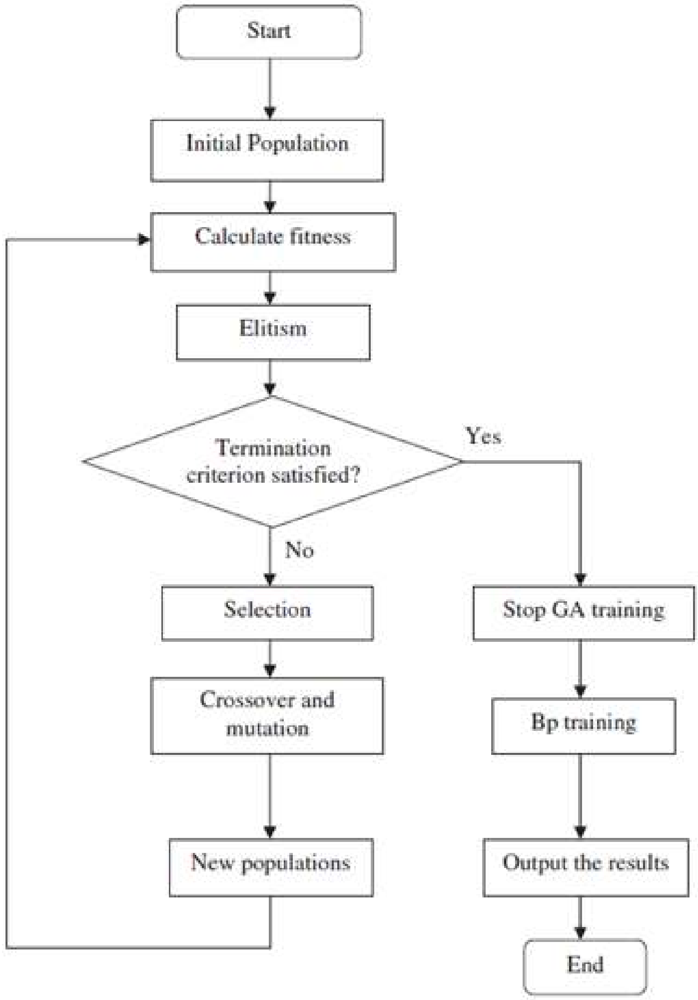

Figure 7: The flowchart of ANN optimized with genetic algorithm (GA-ANN)

1.6 Review of laser micromachining processes parameters optimization review

Conventional machining processes are not able to produce new materials which are being introduced to industrial applications. Modern machining processes play a significant role in industrial growth of new materials due to their ability to produce quality components. The industries are widely using various modern machining processes to tackle new usage requirements. Electric discharge machining (EDM), abrasive jet machining (AJM), ultrasonic machining (USM), electrochemical machining (ECM) and laser beam machining (LBM) are most usable modern machining processes. These processes are much more suitable for special applications and every particular principle of these modern machining process puts some limitations on their uses.

For instance, application of hard and brittle materials, typically represented by advanced ceramics, for a number of high-performance components have recently generated high interest because they have superior mechanical, thermal and physical properties. Because of these special qualities, advanced ceramics are used in wide verity of applications such as turbine blades, valves and valve seats, bearing, heat exchanger and many engineering components.

As a matter of fact, modern machining of new materials is always difficult because of their intrinsic properties like hardness and brittleness. When attempting to machine new materials it is important to carry out damage free machining operations. Since there are numerous parameters that could influence machining processes, it becomes much more complicated to attempt to optimize modern machining processes.

Previously, production engineers used trial-and-error to determine optimal process parameters setting for various process parameters. Trial-and-error method is costly and time consuming. Besides, the optimum process parameters may not be achievable by this method. Application of Trial-and-error method is unsuitable when one of the process parameter variables is continuous and it cannot help engineers to obtain optimal results for process parameter settings.

Deep understanding of modern machining processes and fine tuning various process parameters are two key points to gain damage free products. Therefore, a comprehensive optimization methodology should be done to ensure achieving desired properties.

Table 1 shows different optimization methodologies which researchers have utilised to enhance various modern machining processes.

Authors	Materials	Machining Type	Optimization Techniques	Optimization Goal(s)	Year	Ref
Kansal et al.	AISI-D2 die steel	Powder-mixed EDM	Taguchi method	Machining rate	2007	41
Dhar et al.	Aluminium alloy and SiCP composite	EDM	Linear programming, DOE	MRR Tool wear rate Radial over cut	2007	42
Tzeng and Chen	Tool steel SKD11	EDM	Taguchi-fuzzy-based Approach	Precision and accuracy	2007	43
Yan and Fang	-	Micro-Wire-EDM	GA-based fuzzy logic Controller	Wire tension Wire feed	2008	44
Tzeng	EDM Tool steel SKD11	EDM	Taguchi method	Surface roughness Geometrical accuracy	2008	45
Salman and Kayacan	DIN 1.2379 grade cold work steel	EDM	Genetic expression programming (GEP), Taguchi method	Surface roughness	2008	46
Sundaram et al	A2 tool steel	Micro-EDM	Taguchi method	MRR Tool wear	2008	47
Markopoulos et al	Mild steel, alloyed steels (C45 and 100Cr6), micro-alloyed steel and dual-phase steel	EDM	Artificial neural network (ANN)	Surface roughness	2008	48
Chiang	Al2O3 + TiC mixed ceramic	EDM	Response surface methodology (RSM)	MRR Electrode wear ratio Surface roughness	2008	49
Assarzadeh and Ghoreishi	BD3 steel	Die-sinking EDM	ANN and augmented-Lagrange multiplier algorithm	MRR	2008	50
Kanagarajan et al	WC/Co cemented carbide	Die-sinking EDM	RSM	MRR Surface roughness	2008	51
Saha et al	Tungsten carbide–cobalt Composite	WEDM	ANN	Cutting speed Surface roughness	2008	52
Rao and Pawar	Oil hardened and nitride steel (OHNS)	WEDM	ABC	Cutting speed	2009	53
Chattopadhyay et al	EN-8 carbon steel	Rotary EDM	Taguchi method and linear regression analysis	MRR Electrode wear ratio Surface roughness	2009	54
Rao et al	Ti6Al4V, HE15, 15CDV6 and M-250	EDM	ANN and GA	Surface roughness	2009	55

Saha and Choudhury	EN32 Mild steel	Dry EDM	RSM	MRR Surface roughness Tool wear rate	2009	56
Habib	Al/SiC MMC	EDM	RSM	MRR Tool wear rate Response gap size	2009	57
Sohani et al	Medium carbon steel	EDM	RSM	Surface roughness MRR Tool wear rate	2009	58
Kung et al	Cobalt-bonded tungsten carbide (94WC-6Co)	Powder-mixed EDM	RSM	MRR Electrode wear ratio	2009	59
Taweel	CK45Steel	Die-sinking EDM	RSM	MRR Electrode wear ratio	2009	60
Patel et al	Al2O3/SiCw/TiC ceramic Composite	EDM	RSM and trust region method	Surface roughness	2009	61
Pradhan and Bhattacharyya	Titanium super alloy Ti- 6Al-4V	Micro-EDM	ANN and RSM	MRR Tool wear rate Overcut	2009	62
Maji and Pratihar	Mild steel	Die-sinking EDM	Adaptive network-based fuzzy inference system	MRR Surface roughness	2010	63
Chen et al	Pure tungsten	WEDM	ANN integrated with SA approach	Surface roughness Cutting velocity	2010	64
Pradhan and Biswas	AISI D2 steel	Die-sinking EDM	ANN and neuro-fuzzy approach	MRR Tool wear rate – Radial overcut	2010	65
Patel et al	Al2O3–SiCw–TiC	EDM	Taguchi method and grey relation analysis	MRR Surface roughness	2010	66
Kao et al	Ti–6Al–4V alloy	EDM	Taguchi method and grey relation analysis	Electrode wear ratio MRR Surface roughness	2010	67
Ponappa	Microwave-sintered magnesium nano composite	EDM	Taguchi method	Surface finish Hole taper	2010	68
Kumar et al	EN-24 tool steel	Abrasive-mixed EDM process	Grey relational analysis	MRR Surface roughness	2010	69
Chen et al	ZrO2 Ceramic	EDM	Taguchi method	MRR Electrode wear rate Surface roughness	2010	70
Joshi and Pande	AISI P20 mold steel	Die-sinking EDM	Integrated approach of finite element method (FEM), ANN and GA	Crater size MRR Tool wear rate	2011	71

Prabhu and Vinayagam	Inconel-825 material	EDM	Taguchi method	Surface roughness	2011	72
Sanchez et al	AISI-1045 steel	EDM	RSM	MRR Electrode wear rate Surface roughness	2011	73
Maji and Pratihar	Mild steel	Die-sinking EDM	GA, NSGA-II	MRR Surface roughness	2011	74
Kondayya and Krishna	Hard metal alloys and MMC	WEDM	Genetic programming and NSGA-II	MRR Surface roughness	2011	75
Amini et al	TiB2 nano-composite Ceramic	WEDM	Combination of Taguchi method, ANN and GA	MRR Surface roughness	2011	76
Tzeng et al	Pure tungsten	WEDM	RSM, back-propagation neural network and GA	MRR Surface roughness	2011	77
Rao and Kalyankar	Oil hardened and nitride steel (OHNS)	WEDM	TLBO	Cutting speed	2012	78
Singh	6061Al/Al2O3p/20P aluminium MMC	EDM	Taguchi method and grey relational analysis	MRR Tool wear rate Surface roughness	2012	79
Ay et al	Nickel-based Inconel 718 super alloy	Micro-EDM	Grey relational analysis	Hole taper ratio Hole dilation	2012	80
Yang et al	Tungsten	WEDM	Combination of RSM, ANN and SA algorithm	MRR Average roughness Corner deviation	2012	81
Lingadurai et al	AISI 304 stainless steel	WEDM	DOE	MRR Kerf width Surface roughness	2012	82
Azad and Puri	Titanium alloy	Micro-EDM	Taguchi method	MRR Tool wear rate Overcut	2012	83
Mahardika	Polycrystalline diamond	Micro-EDM	Taguchi method	MRR Tool electrode wear Surface roughness	2012	84
Fonda et al	Polycrystalline diamond Microtools	WEDM	DOE	Productivity Surface roughness	2012	85
Somashekhar	Aluminium	Micro-EDM	SA algorithm	MRR Overcut Surface roughness	2012	86
Lin et al	SK3 carbon tool steel	Micro-EDM	RSM	Electrode wear MRR Overcut	2012	87

Paul et al	γ-titanium aluminide alloy	Dry micro-EDM, Oil micro- EDM	Taguchi method	Overcut	2012	88
Kumar and Agarwal	High-speed steel (M2, SKH9)	Die-sinking EDM	ANN and NSGA	MRR Surface roughness	2012	89
Bhattacharya et al	EN31, H11, and high carbon high chromium (HCHCr) die steel	WEDM	Taguchi method	MRR Surface roughness	2012	90
Puertas and Luis	Hot-pressed B4C, cobaltbonded tungsten carbide ceramic	Die-sinking EDM	DOE and multiple linear regression analysis	Surface roughness Volumetric electrode wear MRR	2012	91
Shrivastava and Dubey	Copper–iron–graphite MMC	Electric discharge diamond grinding	ANN, GA and grey relational analysis	MRR Wheel wear rate	2012	92
Baraskar et al	EN-8 carbon steel	die-sinking EDM	RSM and NSGA-II	MRR Surface – roughness	2012	93
Mukherjee and Chakraborty	Die Steel Particle reinforced aluminium alloy matrix composite	EDM	Biogeography-based optimization (BBO) algorithm	Surface roughness Surface crack density White layer thickness MRR Tool wear rate Gap size Surface finish	2012	94
Shahali et al	DIN 1.4542 stainless steel Alloy	Micro-GA	Shahali et al	Surface roughness Thickness of white layer	2012	95
Kuar et al.	zirconia (ZrO2) ceramics	Laser Microdrilling	RSM	HAZ thickness Taper	2006	96
Kuar et al.	alumina-aluminium interpenetrating phase composite	Laser Microdrilling	RSM	HAZ Thickness Taper	2007	97
Dhupal et al.	Al2TiO5 ceramic	Laser Microgrooving	RSM, ANN	Upper Width Lower Width Depth of Trapezoidal Microgrooves.	2007	98
Dhupal et al.	Aluminum oxide ceramic Al2O3	Laser turned Microgrooving	RSM	Upper Deviation Lower Deviation Depth Characteristics	2008	99
Dubey and Yadava	Aluminum oxide ceramic Al2O3	Laser Cutting	Taguchi method	Kerf Deviation Kerf Width	2008	100
Dhupal et al.	aluminum titanate (Al2TiO5) ceramics	Laser Microgrooving	RSM	deviation of taper deviation of depth characteristics	2008	101
Caydas and Hascalık,	St-37 steel	Laser Cutting	Grey Relational Analysis	Surface Roughness Top kerf Width Width of HAZ	2008	102

Ciurana et al.	Hardened AISI H13 Steel	Laser Micromachining	ANN, PSO	Surface Roughness Volume Error	2009	103
Dhupal et al.	Ceramic	Laser turned Microgrooving	RSM, ANN, GA	Square Micro-grooves	2009	104
Rao and Yadava	nickel-based superalloy	Laser Cutting	Grey Relational Analysis	Kerf Width Kerf Taper Kerf Deviation	2009	105
Sivarao et al.	mild steel	Laser Machining	RSM	Surface Roughness	2010	106
Doloi et al.	aluminium titanate (Al2TiO5)	Laser Microgrooving	RSM	Taper Angles of Micro-grooves	2010	107
Kuar et al.	die steel	Laser Micromachining	RSM	Height of the Recast Layer Depth of the Microgroove	2010	108
Sharma et al.	nickel based superalloy	Laser Cutting	Taguchi method	Kerf Width Kerf Taper Kerf Deviation	2010	109
Biswas et al.	gamma-titanium aluminide	Laser Microdrilling	RSM	Hole Circularity at Exit Taper of the hole	2010	110
Kibria et al.	alumina ceramic	Laser Micro-turning	Experimental Analysis	Depth of Cut Surface Roughness	2010	111
Biswas et al.	Tin-Al2O3 composites	Laser Microdrilling	RSM	Hole Circularity Taper	2010	112
Biswas et al.	TiN-Al2O3 composites	Laser Microdrilling	RSM	Hole Circularity	2010	113
Panda et al.	high carbon steel	Laser Microdrilling	Grey Relational Analysis	HAZ Hole Circularity MRR	2010	114
Kuar et al.	die steel	Laser Micromachining	RSM	Recast Layer Depth of the Microgroove.	2010	115
Sibalija et al.	Ni-based superalloy	Laser Microdrilling	Taguchi method, ANN, GA	quality characteristics of the holes	2011	116
Teixidor et al.	AISI H13 tool steel	Laser Milling	PSO	Surface Quality Dimensional Accuracy	2012	117
Phipon and Pradhan	Al-alloy sheet	Laser Micromachining	RSM, GA	Kerf Taper Surface Roughness.	2012	118
Satapathy et al.	medium carbon steel	Laser Drilling	Taguchi method	Hole Circularities HAZ Aspect Ratio Spatter Deposition	2012	119

Teixidor et al.	316L Stainless Steel	Laser Milling	DOE	Diameter Depth Volume Error	2013	120
Mukherjee et al.	zirconia (ZrO2) ceramics	Laser Micromachining	Artificial Bee Colony Algorithm	HAZ thickness Taper	2013	121
Madić et al.	structural steel S355J2G3 EN 10025 sheet	Laser Cutting	Taguchi method Dual Response Surface Methodology	Average Surface Roughness	2014	122
KantRishi et al.	PMMA (Poly methyl metha acrylate)	Laser Micromachining	RSM	Dimensional Precision Surface Roughness	2015	123
Tshabalala et al.	Si3N4	Laser Micromachining	Numerical and Experimental Approaches	Surface Interaction Time Surface Roughness.	2015	124
Stolberga1 et al.	SUS304 stainless steel, polycarbonate polymer	Laser Cutting	Experimental Analisis	Edge Quality Ablation Rate	2015	125
Biswas et al.	alumina-aluminium interpenetrating phase composite	Laser Microdrilling	RSM	Hole Diameter at Entry Hole Diameter at Exit Hole Taper	2015	126
Giorleo et al.	titanium sheet	Laser Micromachining	Regression Model	Bottom Surface Quality	2015	127
Butkus et al.	soda-lime glass and stainless steel	Femtosecond Ablation	DOE	Fabrication Duration for Cutting	2015	128
Madić et al.	AISI 304 stainless	Laser Cutting	Taguchi method, ANN, GA	Surface Roughness Kerf Width HAZ	2015	129
Rao et al.	T700S CFRP	Laser Cutting	RSM	Kerf Width Taper Percentage HAZ	2016	130

1.7 Conclusion

Modelling and optimization techniques such as DOE (Response Surface Methods and Taguchi), ANN, GA, and PSO and mixed techniques are commonly used in engineering applications especially in laser micromachining process. These approaches are presented and explained in this chapter. By presenting different applied modelling methods in Table 1 it is obvious that these techniques are widely used in different engineering processes. The adaptation of these methods is rising as a useful tool for modelling, predicting and optimizing the processes.

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