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.

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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 \[ y = f(x_1, x_2, x_3, ..., x_k) \]

\[ y = a_0 + \sum a_i x_i + \sum a_{ij} x_i x_j \]
\[ + \sum a_{ii} x_i^2 + \varepsilon \]

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 \[ y = f(x_1, x_2, x_3, ..., x_k) \]. A description of the general RSM procedure can be found in \[ y = f(x_1, x_2, x_3, ..., x_k) \] 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), SNL. To optimize the system when the response is minimum, “Smaller is better” state is considered that can be calculated by Equation (4), SNs.

\[ SN_L = -10 \log \left[ \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right] \]

\[ SN_S = -10 \log \left[ \frac{1}{n} \sum_{i=1}^{n} y_i^2 \right] \]

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.

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.

\[ u = \sum_{j=1}^{m} w_j x_j \]  
\[ V = u + b \]  
\[ y = \varphi(v) \]

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. \( \varphi \) 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.

\[ f(x) = \frac{1}{1 + e^{-\tau}} \]

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.
1.3.2.1 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.
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.](image)

**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 backpropagation 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 employ 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 \( X_i = (x_{i1}, x_{i2}, ..., x_{i3}) \). The velocity of this particle can be represented by another n-dimensional vector \( V_i = (v_{i1}, v_{i2}, ..., v_{in}) \). 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 \( P_i = (p_{i1}, p_{i2}, ..., p_{in}) \). The position of the best individual of the whole swarm is noted as the global best position \( G = (g_{i1}, g_{i2}, ..., g_{in}) \). At each step, the velocity of particle and its new position will be assigned according to the following two equations:

\[
V_i = \omega \cdot V_i + c_1 \cdot r_1 \cdot (P_i - X_i) + c_2 \cdot r_2 \cdot (G - X_i) \tag{9}
\]

\[
X_i = X_i + V_i \tag{10}
\]

where, \( \omega \) 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).
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  |
| Authors                  | Material                          | Process     | Method         | Response Variables | Year | Reference |
|-------------------------|-----------------------------------|-------------|----------------|--------------------|------|-----------|
| Saha and Choudhury      | EN32 Mild steel                   | Dry EDM     | RSM            | MRR Surface roughness | 2009 | 56        |
|                         |                                   |             |                | Tool wear rate     |      |           |
| Habib                  | Al/SiC MMC                        | EDM         | RSM            | MRR Tool wear rate  | 2009 | 57        |
|                        |                                   |             |                | Response gap size  |      |           |
| Sohani et al           | Medium carbon steel               | EDM         | RSM            | Surface roughness  | 2009 | 58        |
|                        |                                   |             |                | MRR                |      |           |
|                        |                                   |             |                | Tool wear rate     |      |           |
| 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  | 2009 | 62        |
|                        |                                   |             |                | Overcut            |      |           |
| Maji and Pratihar      | Mild steel                        | Die-sinking EDM | Adaptive network-based fuzzy inference system | Surface roughness | 2010 | 63        |
| Chen et al             | Pure tungsten                     | WEDM        | ANN integrated with SA approach | Surface roughness | 2010 | 64        |
|                        |                                   |             |                | Cutting velocity   |      |           |
| Pradhan and Biswas     | AISI D2 steel                     | Die-sinking EDM | ANN and neuro-fuzzy approach | MRR Tool wear rate | 2010 | 65        |
|                        |                                   |             |                | – Radial overcut   |      |           |
| 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 | 2010 | 67        |
|                        |                                   |             |                | MRR Surface roughness |      |           |
| 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 | 2010 | 70        |
|                        |                                   |             |                | Surface roughness  |      |           |
| Joshi and Pande        | AISI P20 mold steel               | Die-sinking EDM | Integrated approach of finite element method (FEM), ANN and GA | Crater size | 2011 | 71        |
|                        |                                   |             |                | MRR Tool wear rate  |      |           |
| Authors                  | Material                                | Process     | Method                  | Parameters                  | Year | Page |
|-------------------------|-----------------------------------------|-------------|-------------------------|-----------------------------|------|------|
| Prabhu and Vinayagam   | Inconel-825 material                    | EDM         | Taguchi method          | MRR, Surface roughness      | 2011 | 72   |
| Sanchez et al           | AISI-1045 steel                         | EDM         | RSM                     | Electrode wear rate         | 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   |
| Somashekar              | 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   |
| Authors                  | Material Description                                      | Process Type          | Methodology                  | Response Variables              | Year | Measure |
|--------------------------|-----------------------------------------------------------|-----------------------|------------------------------|---------------------------------|------|---------|
| 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                             | 2012 | 89      |
| Bhattacharya et al       | EN31, H11, and high carbon high chromium (HCHCr) die steel | WEDM                  | Taguchi method               | MRR                             | 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                             | 2012 | 92      |
| Baraskar et al           | EN-8 carbon steel                                         | die-sinking EDM       | RSM and NSGA-II              | Surface roughness, MRR          | 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 Hascalik,     | St-37 steel                                              | Laser Cutting         | Grey Relational Analysis     | Surface Roughness, Top kerf Width, Width of HAZ | 2008 | 102     |
| Authors               | Material/Process                        | Methodologies                           | Response Variables                  | Year | Page |
|----------------------|-----------------------------------------|-----------------------------------------|-------------------------------------|------|------|
| Ciurana et al.       | Hardened AISI H13 Steel                 | Laser Micromachining                    | ANN, PSO                            | 2009 | 103  |
| Dhupal et al.        | Ceramic                                 | Laser turned Microgrooving              | RSM, ANN, GA                        | 2009 | 104  |
| Rao and Yadava       | nickel-based superalloy                 | Laser Cutting                           | Grey Relational Analysis            | 2009 | 105  |
| Sivarao et al.       | mild steel                              | Laser Machining                         | RSM                                 | 2010 | 106  |
| Doloi et al.         | aluminium titanate (Al2TiO5)            | Laser Micromachining                    | RSM                                 | 2010 | 107  |
| Kuar et al.          | die steel                               | Laser Micromachining                    | RSM                                 | 2010 | 108  |
| Sharma et al.        | nickel based superalloy                 | Laser Cutting                           | Taguchi method                      | 2010 | 109  |
| Biswas et al.        | gamma-titanium aluminate                | Laser Microdrilling                     | RSM                                 | 2010 | 110  |
| Kibria et al.        | alumina ceramic                         | Laser Micromachining                    | Experimental Analysis              | 2010 | 111  |
| Biswas et al.        | Tin-Al2O3 composites                    | Laser Microdrilling                     | RSM                                 | 2010 | 112  |
| Biswas et al.        | TiN-Al2O3 composites                    | Laser Microdrilling                     | RSM                                 | 2010 | 113  |
| Panda et al.         | high carbon steel                       | Laser Microdrilling                     | Grey Relational Analysis            | 2010 | 114  |
| Kuar et al.          | die steel                               | Laser Micromachining                    | RSM                                 | 2010 | 115  |
| Sibalija et al.      | Ni-based superalloy                     | Laser Microdrilling                     | Taguchi method, ANN, GA             | 2011 | 116  |
| Teixidor et al.      | AISI H13 tool steel                     | Laser Milling                           | PSO                                 | 2012 | 117  |
| Phipon and Pradhan   | Al-alloy sheet                          | Laser Micromachining                    | RSM, GA                             | 2012 | 118  |
| Satapathy et al.     | medium carbon steel                     | Laser Drilling                          | Taguchi method                      | 2012 | 119  |
| Authors           | Material/Composite | Process                    | Methodology/Algorithm | Parameter(s)                      | Year | Value |
|-------------------|--------------------|----------------------------|------------------------|-----------------------------------|------|-------|
| Teixidor et al.   | 316L Stainless Steel | Laser Milling             | DOE                    | Diameter, Depth, Volume Error     | 2013 | 120   |
| Mukherjee et al.  | 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   |
| Stolbergal et al. | SUS304 stainless steel, polycarbonate polymer | Laser Cutting            | Experimental Analysis  | Hole Diameter at Entry, Hole Diameter at Exit, Hole Taper | 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.

References

1. Antony, J., Design of experiments for engineers and scientists, 2003: Butterworth-Heinemann.
2. Katayama, S. and A. Matsunawa, Solidification Behaviour and Microstructural Characteristics of Pulsed and Continuous Laser Welded Stainless Steels. IFS(Publications) Ltd, 1986: p. 19-25.
3. Cochran, W.G. and G.M. Cox, Experimental designs. 1957.
4. Eriksson, L., Design of experiments: principles and applications, 2008: MKS Umetrics AB.
5. Benyounis, K., Prediction and optimization of residual stresses, weld-bead profile and mechanical properties of laser welded components, 2006, PhD Thesis, Dublin City University.
6. Box, G.E.P. and K. Wilson, On the experimental attainment of optimum conditions. Journal of the Royal Statistical Society. Series B (Methodological), 1951. 13(1): p. 1-45.
7. http://cms3.minitab.co.kr/board/minitab_data/7.%20DesignofExperimentsAllTopics.pdf. Design of Experiments. 2005 [cited December-2012].
8. Montgomery, D.C., Design and analysis of experiments, 2008: Wiley.
9. Moradi, M., et al., Enhancement of low power CO 2 laser cutting process for injection molded polycarbonate. Optics & Laser Technology, 2017. 96: p. 208-218.
10. Moradi, M. and E. Golchin, Investigation on the Effects of Process Parameters on Laser Percussion Drilling Using Finite Element Methodology; Statistical Modelling and Optimization. Latin American Journal of Solids and Structures, 2017. 14(3): p. 464-484.
11. Abdollahi, H., et al., Investigation of green properties of iron/jet-milled grey cast iron compacts by response surface method. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2014. 228(4): p. 493-503.
12. Khuri, A.I. and J.A. Cornell, Response surfaces: designs and analyses,. Vol. 152. 1996: CRC.
13. www.academic.marist.edu/~jzbv/architecture/Projects/S2002/NeuralNet2/COA.PPT. Collins, M. and A. DeLucca, Neural Networks. 2010 [cited June-2012].
14. Callan, R., Essence of neural networks,1998: Prentice Hall PTR.
15. Haykin, S., Neural networks: a comprehensive foundation,2008: Prentice Hall.
16. Bowen, W.R., M.G. Jones, and H.N.S. Yousef, Prediction of the rate of crossflow membrane ultrafiltration of colloids: A neural network approach. Chemical engineering science, 1998. 53(22): p. 3793-3802.
17. Varoonchotikul, P., Flood forecasting using artificial neural networks, Taylor & Francis, 2003: Balkema Rotterdam, The Netherlands.
18. Singh, Y. and P. Kumar, Application of feed-forward neural networks for software reliability prediction. SIGSOFT Software Engineering Notes, 2010. 35(5): p. 1-6.
19. Ahmad, A.M., S. Ismail, and D. Samaon. Recurrent neural network with backpropagation through time for speech recognition. in International Symposium Communications and Information Technology, ISCIT. 2004.
20. Nagesh Kumar, D., K. Srinivasa Raju, and T. Sathish, River flow forecasting using recurrent neural networks. Water resources management, 2004. 18(2): p. 143-161.
21. Kshirsagar, A. and M. Rathod. Artificial Neural Network. in IJCA Proceedings on Recent Trends in Computing. 2012. Foundation of Computer Science (FCS).
22. Ní Mhurchú, J., Dead-end and crossflow microfiltration of yeast and bentonite suspensions: experimental and modelling studies incorporating the use of artificial neural networks, 2008, Dublin City University.
23. Aydiner, C., I. Demir, and E. Yildiz, Modeling of flux decline in crossflow microfiltration using neural networks: the case of phosphate removal. Journal of membrane science, 2005. 248(1): p. 53-62.
24. Rumelhart, D.E., G.E. Hinton, and R.J. Williams, Learning representations by back-propagating errors. Cognitive modeling, 2002. 1: p. 213.
25. Duda, R.O., P.E. Hart, and D.G. Stork, Pattern classification. 2nd ed. New York 2001.
26. Fu, R.Q., T.W. Xu, and Z.X. Pan, Modelling of the adsorption of bovine serum albumin on porous polyethylene membrane by back-propagation artificial neural network. Journal of membrane science, 2005. 251(1): p. 137-144.
27. Amari, S., et al., Asymptotic statistical theory of overtraining and cross-validation. Neural Networks, IEEE Transactions on, 1997. 8(5): p. 985-996.
28. Maier, H.R. and G.C. Dandy, Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental modelling & software, 2000. 15(1): p. 101-124.
29. Kennedy, J. and R. Eberhart, Particle swarm optimization 1995 IEEE International Conference on Neural Networks Proceedings, 1942, Vols.
30. Shi, Y. and R. Eberhart. A modified particle swarm optimizer. in Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on. 1998. IEEE.
31. Eberhart, R.C. and Y. Shi. Comparison between genetic algorithms and particle swarm optimization. in International conference on evolutionary programming. 1998. Springer.
32. Shial, R.K., K.H.K. Reddy, and K. Narayana. An Optimal RPC Based Approach to Increase Fault in Wireless Ad-Hoc Network. in International Conference on Computer Science and Information Technology. 2012. Springer.
33. ZhuoKang, Z.H. and Y. Liu, Computational Intelligence and Intelligent Systems.
34. Hamedi, M. and M. Bisepar. Application of a Hybrid of Artificial Intelligence for Optimization Part Dimensional Contradictions in Plastic Injection Process. 2006. ANNUAL INTERNATIONAL MECHANICAL ENGINEERING CONFERENCE.

35. Spina, R., Optimisation of injection moulded parts by using ANN-PSO approach. Journal of Achievements in Materials and Manufacturing Engineering, 2006. 15(1-2): p. 146-152.

36. Melabadi, M.S. and F. Sharifi, Optimization of Plastic Injection Molding Process by Combination of Artificial Neural Network and Genetic Algorithm. Journal of Optimization in Industrial Engineering, 2013. 6(13): p. 49-54.

37. Shen, C., L. Wang, and Q. Li, Optimization of injection molding process parameters using combination of artificial neural network and genetic algorithm method. Journal of materials processing technology, 2007. 183(2): p. 412-418.

38. Kurtaran, H., B. Ozelcelik, and T. Erzurumlu, Warpage optimization of a bus ceiling lamp base using neural network model and genetic algorithm. Journal of materials processing technology, 2005. 169(2): p. 314-319.

39. Ozelcelik, B. and T. Erzurumlu, Comparison of the warpage optimization in the plastic injection molding using ANOVA, neural network model and genetic algorithm. Journal of materials processing technology, 2006. 171(3): p. 437-445.

40. Bharti, P. and M. Khan, Recent methods for optimization of plastic injection molding process-A retrospective and literature review. 2010.

41. Kansal, HK., et al., Effect of silicon powder mixed EDM on machining rate of AISI D2 die steel. Manuf Process, 2007. 9: p. 13–22

42. Dhar, S., et al., Mathematical modeling of electric discharge machining of cast Al–4Cu–6Si alloy–10 wt.% SiCP composites. Mater Process Technol, 2007. 194: p. 24–29

43. Tzeng, YF. and Chen, FC., Multi-objective optimisation of high speed electrical discharge machining process using a Taguchi fuzzy based approach. Mater Des, 2007. 28: p. 1159–1168

44. Yan, MT. and Fang, CC., Application of genetic algorithm-based fuzzy logic control in wire transport system of wire-EDM machine. Mater Process Technol, 2008. 205: p. 128–137

45. Tzeng, YF., Development of a flexible high-speed EDM technology with geometrical transform optimization. Mater Process Technol, 2008. 203: p. 355–364

46. Salman, O. and Kayacan, MC., Evolutionary programming method for modeling the EDM parameters for roughness. Mater Process Technol, 2008. 200: p. 347–355

47. Sundaram, MM., et al, A study on process parameters of ultrasonic assisted micro EDM based on Taguchi method. Mater Eng Perform, 2008. 17(2): p. 210–215

48. Markopoulos, AP., et al., Artificial neural network models for the prediction of surface roughness in electrical discharge machining. Intell Manuf, 2008. 19: p. 283–292

49. Chiang, KT., Modeling and analysis of the effects of machining parameters on the performance characteristics in the EDM process of Al2O3 + TiC mixed ceramic. Int J Adv Manuf Technol, 2008. 37: p. 523–533

50. Assarzadeh, S. and Ghoreishi, M., Neural-network-based modeling and optimization of the electro-discharge machining process. Int J Adv Manuf Technol, 2008. 39: p. 488–500

51. Kanagarajan, D., et al., Optimization of electrical discharge machining characteristics of WC/Co composites using non-dominated sorting genetic algorithm (NSGA-II). Int J Adv Manuf Technol, 2008. 36: p. 1124–1132
52. Saha, P., et al., Soft computing models based prediction of cutting speed and surface roughness in wire electro-discharge machining of tungsten carbide cobalt composite. Int J Adv Manuf Technol, 2008. 39: p. 74–84

53. Rao, RV. and Pawar, PJ., Modelling and optimization of process parameters of wire electrical discharge machining. J Eng Manuf , 2009. 223(11): p. 1431–1440

54. Chattopadhyay, KD., et al., Development of empirical model for different process parameters during rotary electrical discharge machining of copper–steel (EN-8) system. J Mater Process Technol, 2009. 209: p. 1454–1465

55. Rao, GKM., et al., Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm. J Mater Process Technol, 2009. 209: p. 1512–1520

56. Saha, SK. and Choudhury SK., Experimental investigation and empirical modeling of the dry electric discharge machining process. Int J Mach Tool Manuf, 2009. 49: p. 297–308

57. Habib, SS., Study of the parameters in electrical discharge machining through response surface methodology approach. Appl Math Model, 2009. 33: p. 4397–4407

58. Sohani, MS., et al., Investigations into the effect of tool shapes with size factor consideration in sink electrical discharge machining (EDM) process. Int J Adv Manuf Technol, 2009. 45: p. 1131–1145

59. Kung, KY., et al., Material removal rate and electrode wear ratio study on the powder mixed electrical discharge machining of cobalt-bonded tungsten carbide. Int J Adv Manuf Technol, 2009. 40: p. 95–104

60. Taweel, TAE., Multi-response optimization of EDM with Al– Cu–Si–TiC P/M composite electrode. Int J Adv Manuf Technol, 2009. 44: p. 100–113

61. Patel, KM., et al., Determination of an optimum parametric combination using a surface roughness prediction model for EDM of Al2O3/SiCw/TiC ceramic composite. Mater Manuf Process, 2009. 24: p. 675–682

62. Pradhan, BB. and Bhattacharyya B., Modelling of micro electrodischarge machining during machining of titanium alloy Ti–6Al–4V using response surface methodology and artificial neural network algorithm. Eng Manuf, 2009. 223(6): p. 683–693

63. Maji, K. and Pratihar DK., Forward and reverse mappings of electrical discharge machining process using adaptive network based fuzzy inference system. Expert Syst Appl, 2010. 37: p. 8566–8574

64. Chen, HC., et al., Optimization of wire electrical discharge machining for pure tungsten using a neural network integrated simulated annealing approach. Expert Syst Appl, 2010. 37: p. 7147–7153

65. Pradhan, MK. and Biswas, CK., Neuro-fuzzy and neural network-based prediction of various responses in electrical discharge machining of AISI D2 steel. Int J Adv Manuf Technol, 2010. 50: p. 591–610

66. Patel, KM., et al., Optimisation of process parameters for multi-performance characteristics in EDM of Al2O3 ceramic composite. Int J Adv Manuf Technol, 2010. 47: p. 1137–1147

67. Kao, JY., et al., Optimization of the EDM parameters on machining Ti–6Al–4V with multiple quality characteristics. Int J Adv Manuf Technol, 2010. 47: p. 395–402

68. Ponappa, K., et al., The effect of process parameters on machining of magnesium nano alumina composites through EDM. Int J Adv Manuf Technol, 2010. 46: p. 1035–1042

69. Kumar, A., et al., A study of multiobjective parametric optimization of silicon abrasive mixed electrical discharge machining of tool steel. Mater Manuf Process, 2010. 25: p. 1041–1047
70. Chen, YF., et al., Optimization of electrodischarge machining parameters on ZrO2 ceramic using the Taguchi method. J Eng Manuf, 2010. 224(2): p. 195–205
71. Joshi, SN. and Pande, SS., Intelligent process modeling and optimization of die-sinking electric discharge machining. Appl Soft Comput, 2011. 11: p. 2743–2755
72. Prabhu, S. and Vinayagam, BK., AFM surface investigation of Inconel 825 with multi wall carbon nano tube in electrical discharge machining process using Taguchi analysis. Archives Civil Mech Eng, 2011. 11: p. 149–170
73. Sanchez, HT., et al., Development of an inversion model for establishing EDM input parameters to satisfy material removal rate, electrode wear ratio and surface roughness. Int J Adv Manuf Technol, 2011. 57: p. 189–201
74. Maji, K. and Pratihar DK., Modeling of electrical discharge machining process using conventional regression analysis and genetic algorithms. J Mater Eng Perform, 2011. 20: p. 1121–1127
75. Kondayya, D. and Krishna, AG., An integrated evolutionary approach for modelling and optimization of wire electrical discharge machining. J Eng Manuf, 2011. 225(4): p. 549–567
76. Amini, H., et al., Optimization of process parameters in wire electrical dischargemachining of TiB2 nanocomposite ceramic. J Eng Manuf, 2011. 225(12): p. 2220–2227
77. Tzeng, CJ., et al., Optimization of wire electrical discharge machining of pure tungsten using neural network and response surface methodology. J Eng Manuf, 2011. 225(6): p. 841–852
78. Rao, RV. and Kalyankar, VD., Parameter optimization of modern machining processes using teaching–learning-based optimization algorithm. Eng Appl Artif Intell, 2012. doi:10.1016/j.engappai.2012.06.007
79. Singh, S., Optimization of machining characteristics in electric discharge machining of 6061Al/Al2O3p/20P composites by grey relational analysis. Int J Adv Manuf Technol, 2012. doi:10.1007/s00170- 012-3984-8
80. Ay, M., et al., Optimization of micro-EDM drilling of Inconel 718 superalloy. Int J AdvManuf Technol, 2012. doi:10. 1007/s00170-012-4385-8
81. Yang, RT., et al., Optimization of wire electrical discharge machining process parameters for cutting tungsten. Int J Adv Manuf Technol, 2012. 60: p. 135–147
82. Lingadurai, K., et al., Selection of wire electrical discharge machining process parameters on stainless steel AISI grade-304 using design of experiments approach. J Inst Eng (India): Ser C, 2012. 93(2): p. 163–170
83. Azad, MS. and Puri, AB., Simultaneous optimisation of multiple performance characteristics in micro-EDM drilling of titanium alloy. Int J Adv Manuf Technol, 2012. 61: p. 1231–1239
84. Mahardika, M., et al., The parameters evaluation and optimization of polycrystalline diamond micro-electrodischarge machining assisted by electrode tool vibration. Int J Adv Manuf Technol, 2012. 60: p. 985–993
85. Fonda, P., et al., WEDM condition parameter optimization for PCD microtool geometry fabrication process and quality improvement. Int J Adv Manuf Technol, 2012. doi:10.1007/s00170-012-3977-7
86. Somashekhkar, KP., et al., A feasibility approach by simulated annealing on optimization of micro-wire electric discharge machining parameters. Int J Adv Manuf Technol, 2012. 61: p. 1209–1213
87. Lin, YC., et al., Evaluation of the characteristics of the microelectrical discharge machining process using response surface methodology based on the central composite design. Int J Adv Manuf Technol, 2012. doi:10.1007/s00170-011-3745-0
88. Paul G, et al., Investigations on influence of process variables on crater dimensions in micro-EDM of γ-titanium aluminide alloy in dry and oil dielectric media. Int J Adv Manuf Technol, 2012 doi:10.1007/s00170-012-4235-8
89. Kumar, K. and Agarwal, S., Multi-objective parametric optimization on machining with wire electric discharge machining. Int J Adv Manuf Technol, 2012. doi:10.1007/s00170-011-3833-1
90. Bhattacharya, A., et al., Optimal parameter settings for rough and finish machining of die steels in powder-mixed EDM. Int J Adv Manuf Technol, 2012. 61: p. 537–548
91. Puertas, I. and Luis, CJ. Optimization of EDM conditions in the manufacturing process of B4C andWC-Co conductive ceramics. Int J Adv Manuf Technol, 2012. 59: p. 575–582
92. Shrivastava, PK. and Dubey AK., Intelligent modeling and multiobjective optimization of electric discharge diamond grinding. Mater Manuf Process, 2012. doi:10.1080/10426914.2012.700153
93. Baraskar, SS., et al., Multi-objective optimization of electrical discharge machining process using hybrid method. Mater Manuf Process, 2012. doi:10.1080/10426914.2012.700152
94. Mukherjee, R. and Chakraborty, S., Selection of EDM process parameters using biogeography-based optimization algorithm. Mater Manuf Process, 2012. 27: p. 954–962
95. Shahali, H., et al., Optimization of surface roughness and thickness of white layer in wire electrical discharge machining of DIN 1.4542 stainless steel using micro-genetic algorithm and signal to noise ratio techniques. J Eng Manuf, 2012. 226(5): p. 803–812
96. Kuar, A., et al., Modeling and analysis of pulsed Nd:YAG laser machining characteristics during micro-drilling of zirconia (ZrO2). Int J Machine Tools Mf, 2006. 46: p. 1301–1310.
97. Kuar, AS., et al., Nd:YAG laser micromachining of alumina-aluminium interpenetrating phase composite using response surface methodology. International Journal of Machining and Machinability of Materials, 2006. 1: p. 432–444
98. Dhupal, D., et al., Optimization of process parameters of Nd:YAG laser microgrooving of Al2TiO5 ceramic material by response surface methodology and artificial neural network algorithm. Proc. IMechE, 2007. 221: p. 1341-1351
99. Dhupal, D., et al., Pulsed Nd:YAG laser turning of micro-groove on aluminum oxide ceramic (Al2O3). International Journal of Machine Tools and Manufacture, 2008. 48(2): p. 236–248
100. Dubey, AK. and Yadava, V., Multi-objective optimization of laser beam cutting process. Optics and Laser Technology, 2008. 40(3): p. 562- 570
101. Dhupal, D., et al., Parametric analysis and optimization of Nd:YAG laser microgrooving of aluminium titanate (Al2TiO5) ceramics. International Journal of Advanced Manufacturing Technology, 2008. 36(10): p. 883–893.
102. Çaydaş, U. and Haşçalık., A., Use of the grey relational analysis to determine optimum laser cutting parameters with multi-performance characteristics. Optics and Laser Technology, 2008. 40(7): p. 987-994
103. Ciurana, J., et al., Neural Network Modeling and Particle Swarm Optimization (PSO) of Process Parameters in Pulsed Laser Micromachining of Hardened AISI H13 Steel, Materials and Manufacturing Processes, 2009. 24(3): p. 358-368
104. Dhupal, D., et al., Modeling and optimization onNd:YAGlaser turned micro-grooving of cylindrical ceramic material. Optics and Lasers in Engineering, 2009. 47(9): p. 917–925, 2009.
105. Rao, R. and 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, 2009. 41(8): p. 922–930
106. Sivarao, TJ S., et al., RSM based modeling for surface roughness prediction in laser machining. International Journal of Engineering & Technology, 2010. 10: p. 32–37
107. Doloi, B., et al., Modelling and analysis on machining characteristics during pulsed Nd:YAG laser microgrooving of aluminium titanate (Al2TiO5). International Journal of Manufacturing Technology and Management, 2010. 21(1-2): p. 30–41
108. Kuar, AS., et al., Multi-response optimisation of Nd:YAG laser micro-machining of die steel using response surface methodology. International Journal of Manufacturing Technology and Management, 2010. 21(1-2): p. 17–29
109. Sharma, A., et al., Optimization of kerf quality characteristics during Nd: YAG laser cutting of nickel based superalloy sheet for straight and curved cut profiles. Optics and Laser Engineering, 2010. 48(9): p. 915-925
110. Biswas, R., et al., A parametric study of pulsed Nd:YAG laser micro-drilling of gamma-titanium aluminide. Optics and Laser Technology, 2010. 42 (1): p. 23–31
111. Kibria, G., et al., Experimental analysis on Nd:YAG laser micro-turning of alumina ceramic. International Journal of Advanced Manufacturing Technology, 2010. 50(5–8): p. 643–650
112. Biswas, R., et al., Effects of process parameters on hole circularity and taper in pulsed Nd:YAG laser microdrilling of TiN-Al2O3 composites. Materials and Manufacturing Processes, 2010. 25(6): p. 503–514
113. Biswas, R., et al., Characterization of hole circularity in pulsed Nd:YAG laser micro-drilling of TiN-Al2O3 composites. International Journal of Advanced Manufacturing Technology, 2010. 51(9–12): p. 983–994
114. Panda, S., et al., Determination of optimum parameters with multi-performance characteristics in laser drilling—a grey relational analysis approach. International Journal of Advanced Manufacturing Technology, 2011. 54(9–12): p. 957–967
115. Kuar, AS., et al, Multi-response optimisation of Nd:YAG laser micro-machining of die steel using response surface methodology. International Journal of Manufacturing Technology and Management, 2010. 21(1-2): p. 17–29
116. Sibalija, TV., et al., Multi-response design of Nd:YAG laser drilling of Ni-based superalloy sheets using Taguchi’s quality loss function, multivariate statistical methods and artificial intelligence. International Journal of Advanced Manufacturing Technology, 2011. 54(5–8): p. 537–552, 2011.
117. Teixidor, D., et al., Optimization of process parameters for pulsed laser milling of micro-channels on AISI H13 tool steel. Robotics and Computer-Integrated Manufacturing, 2012. 29(1): p. 209-218
118. Phipon, R. and Pradhan, BB., Control Parameters Optimization of Laser Beam Machining Using Genetic Algorithm. International Journal of Computational Engineering Research. 2012. 2(5): p. 1510-1516
119. Satapathy, BB., et al., Quality Optimization of Micro-Hole In Laser Drilling. IOSR Journal of Engineering, 2012. 2 (3): p. 382-388
120. Teixidor, D., et al., Multiobjective Optimization of Laser Milling Parameters of Microcavities for the Manufacturing of DES, Materials and Manufacturing Processes, 2013. 28(12): p. 1370-1378
121. Mukherjee, R., Parametric Optimization of Nd:YAG Laser Beam Machining Process Using Artificial Bee Colony Algorithm. Journal of Industrial Engineering. 2013. doi:10.1155/2013/570250
122. Madić, M., et al., Optimization of CO2 Laser Cutting Process using Taguchi and Dual Response Surface Methodology. Tribology in Industry, 2014. 36(3): p. 236-243
123. Kant, R., et al., Studies on CO2 Laser Micromachining on PMMA to Fabricate Micro Channel for Microfluidic Applications. Lasers Based Manufacturing, 2015. doi: 10.1007/978-81-322-2352-8_13
124. Tshabalala, LC., et al., Optimization of Spiral Contours for Pulsed Laser Micromachining. Journal of Micro- and Nano-Manufacturing. 2015, doi: 10.1115/1.4030765
125. Stolberg, K., et al., Optimization of laser process conditions for cutting of thin metal and polymer sheets with femtosecond laser. Proc. SPIE 9355, Frontiers in Ultrafast Optics: Biomedical, Scientific, and Industrial Applications XV, 2015. doi: 10.1117/12.2079376
126. Biswas, R., et al., Process optimization in Nd:YAG laser microdrilling of alumina–aluminium interpenetrating phase composite. J Mater Res Technol. 2015. 4(3): p. 323–332
127. Giorleo, L., et al., Optimization of laser micromachining process for biomedical device fabrication. Int J Adv Manuf Technol, 2016. 82: p. 901–907
128. Butkus, S., Analysis of the Micromachining Process of Dielectric and Metallic Substrates Immersed in Water with Femtosecond Pulses. Micromachines, 2015. 6: p. 2010–2022
129. Madić, M., et al., Multi-objective optimization of cut quality characteristic in CO2 laser cutting stainless steel. Technical Gazette, 2015. 4: p. 885-892
130. Rao, SH., et al., Fiber laser cutting of CFRP composites and process optimization through response surface methodology. Materials and Manufacturing Processes, 2016. 32(14): p. 1612-1621