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Review

A review on applications of artificial intelligence in modeling and optimization of laser beam machining

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A B S T R A C T

Laser beam machining (LBM) as an efficient tool for material removal has attracted the attention of manufacturing industries. Accordingly, there is a great motivation in the modeling and optimization of this non-conventional machining process. In this paper, the focus is on the most common LBM process, including cutting, grooving, turning, milling, and drilling. The development of an accurate model between the input and output variables of the LBM process is difficult and complex due to the non-linear behavior of the process under various conditions. In the case of LBM, the input variables are system, material, and process parameters, and the output variables are the quality characteristics of laser machined workpiece, including geometry characteristics, metallurgical characteristics, surface roughness, and material removal rate (MRR). Recently, among computational methods, artificial intelligence (AI) has been studied by scientists as a pioneer in the field of modeling and optimizing quality features of LBM. AI techniques utilize the empirical findings and existing knowledge for modeling, optimization, monitoring, and controlling of the LBM process. In this paper, the applications of AI techniques, including artificial neural network (ANN), fuzzy logic (FL), metaheuristic optimization algorithms, and hybrid approaches in modeling and optimization of the quality characteristics of LBM are reviewed. It is shown that AI techniques are successfully capable of predicting and improving the features of the laser machined workpiece. It is also demonstrated that AI can be used as a powerful tool to obtain a comprehensive model and optimal setting parameters of LBM. In addition, according to the potential and capability of AI techniques, several ideas have been offered for future studies.

1. Introduction

In the current competitive market, companies adopt new manufacturing technologies to obtain high-performance production and high-quality products [1]. Among various production processes, machining has continuously developed to achieve better performance due to its vast applications in fabrication [2,3]. Nowadays, many non-conventional machining methods are used in the industry, including laser beam machining (LBM), plasma beam machining (PBM), ion beam machining (IBM), electron beam machining (EBM), electro discharge machining (EDM), chemical machining (CM), electrochemical machining (EM), jet machining (JM), and Ultrasonic machining (UM) processes. These machining processes are employed to build accurate and intricate shapes in hard-to-machine materials such as titanium, ceramics, and fiber-reinforced composites, which are difficult to process by conventional processes. However, the application of these processes has limitations on geometry accuracy and complexity, type of materials etc. [4]. Selection of an appropriate process for a particular application can be considered as a decision-making problem with several criteria. Among these non-conventional machining technologies, due to the capability of LBM in the machining of a broad range of materials with high precision makes it a specialty machining technology and has always attracted attention [5,6]. The characteristics of LBM include precise cuts, high cutting speed, small heat-affected zone (HAZ), and narrow kerf width [7]. The main advantages and disadvantages of LBM are provided in Fig. 1.

There are generally two main mechanisms in laser material processing - athermal and thermal. In an athermal mechanism, the breaking and making chemical bonds occur via resonant energy transfer without temperature alteration [8]. While the thermal mechanism is generally regarded as a thermal process for material removal with high-energy density at the laser beam focus, which causes heating, melting, and vaporization of the material [9]. In this study, the thermal mechanism is considered as the main process in LBM.

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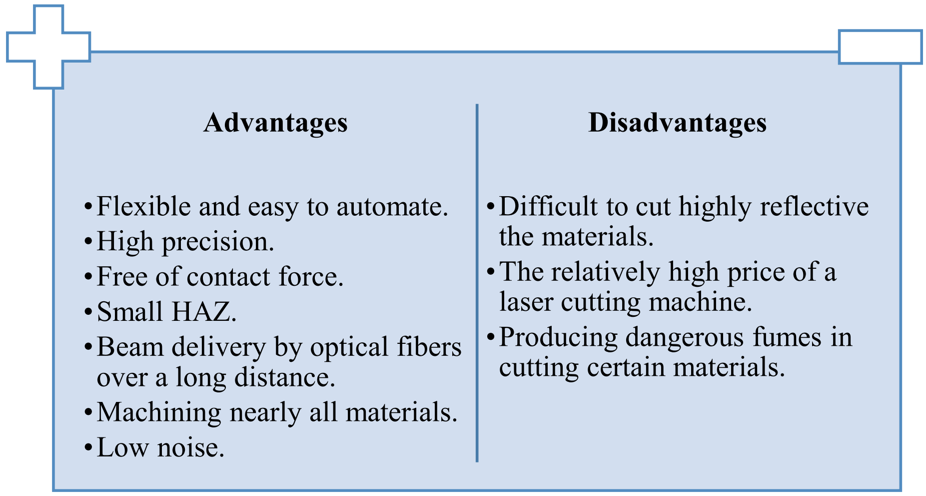


Fig. 1. Advantages and disadvantages of LBM.

Cutting, grooving, turning, milling, and drilling (percussion and trepaning) are the major configurations of LBM. The laser can also be used as an assistant tool for conventional machining such as turning to obtain better machinability by changing the microstructure and softening the surface of the workpiece [10]. The laser beams by heating the workpiece before the main process reduce machining force and enhance the cutting features [11]. It is worth to mention that laser-based processes such as laser remelting, laser hardening, laser cladding, and laser alloying have been widely used in surface engineering applications [12–14].

There are different kinds of lasers with specific characteristics that are designed for various applications. Lasers can be categorized based on their laser medium, including gas (neutral atom lasers, ion lasers, metal vapor lasers, and molecular gas lasers), liquid (dye), and solid-state lasers (the ruby, Neodymium, and semiconductor lasers). Among different types of lasers, CO_2 and Nd:YAG are most commonly employed for LBM due to their appropriate characteristics [15]. CO_2 lasers are molecular gas lasers with 10.6 μm wavelength in the infrared region of the electromagnetic spectrum. Regarding the high mean beam intensity and the quality of the beam in CO_2 lasers, they are suitable for high-speed finishing of sheet metal. Nd:YAG lasers with 1 μm wavelength can be absorbed by highly reflective materials such as aluminum alloys that are hard to machine with CO_2 lasers [16,17]. Although, Nd:YAG lasers have a low beam intensity, high peak intensity while working in pulsed mode enables even thicker materials to be machined. Because of the high peak power and low interaction time in the pulsed mode laser beam, it is recommended for cutting the material with high thermal conductivity [18].

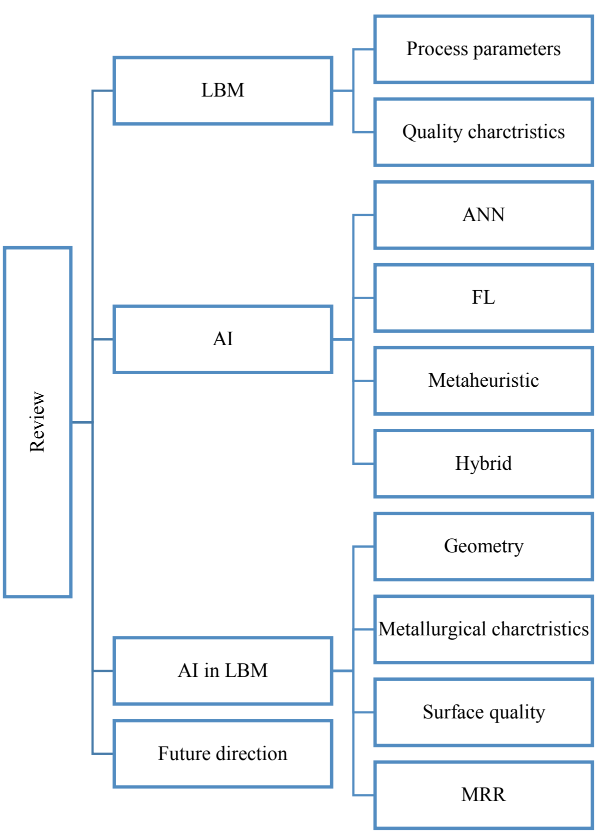


Fig. 2. Hierarchical structure of the contents.

The machining and micromachining of high precision and complex parts that may not be produced by long-pulse lasers are able to be accomplished with the ultrashort pulse lasers [19–21]. Up to now, several models have been proposed to evaluate the basic principle of ablation in the ultrashort laser pulse. For example, Stavropoulos et al. [22] developed an molecular dynamic (MD) model to obtain a temporal evolution of the ablation depth and temperature in terms of the laser fluence. Machining with the ultrashort laser pulses cause limited mechanical and thermal effects on the workpiece. However, the mechanical and thermal effects still play a significant role in the quality characteristics of laser material processing [23]. Likewise, the ultrashort pulse lasers can be applied for precise local heating of the material in some applications such as annealing and welding.

LBM relies on the absorbed energy that raises the substrate temperature to its melting point and beyond [24]. It generally relates to the formation of plasma and optical absorption mechanisms, often result in micro-cracks, thermal deposition, and minor surrounding collateral damage [6]. The maximum depth at which the penetration occurs is called the depth of penetration (where the laser energy is converted to heat). The depth of penetration also depends on the duration of the laser pulses. Due to the low time to diffuse thermal energy in laser with shorter pulses duration, the greater surface temperature is produced [25]. Material removal with long pulse lasers is mainly obtained by melting and evaporating the material with controlled laser power density. However, the removed material often re-deposits near the melted area and forms a recast layer [26]. The linear absorption of nanosecond laser can cause much higher absorption length and melt depth than femtosecond absorption. For opaque materials, the beam absorption is induced by single-photon absorption [27]. In this case, the absorption coefficient is used to determine the penetration depth [28]. For a small

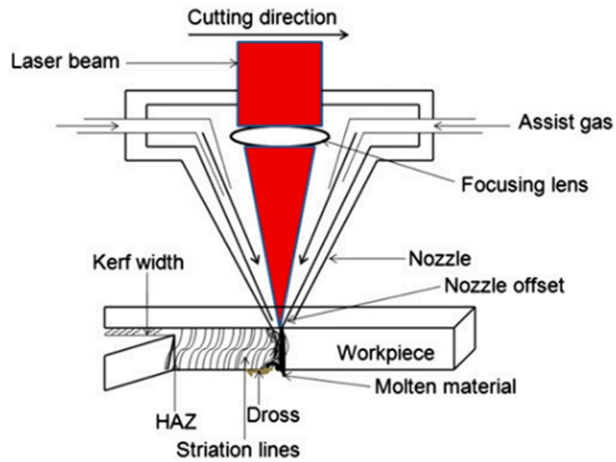


Fig. 3. Schematic of laser beam cutting [37].

absorption coefficient, both non-linear and linear absorption might be lead to a smaller penetration depth in the ultrafast laser [29]. In contrast, for transparent materials, the absorption occurs by non-linear and multi-photon absorption [30,31]. Then, the penetration depth in the nanosecond laser is higher than femtosecond laser owing to a smaller absorption cross-section.

Determination of the proper setting parameters in LBM is essential for achieving optimal machining performance and is of significant interest for both acdemicians and engineers [32]. From a technological point of view, LBM is a complex process that is affected by a large number of parameters [33,34]. The most critical influential parameters associated with LBM are the process parameters, material parameters, and system parameters [35]. In the past few years, researchers have performed different studies to enhance the performance of the LBM by examining the different factors influencing the quality characteristics [36]. Based on the results from theoretical and empirical studies, the performance of laser material processing can be enhanced significantly by choosing the process parameters adequately [37].

Deep understanding of the LBM process and knowing the relation between inputs and outputs parameters of LBM are useful to gain the desired products. There are many control parameters in LBM from discrete to continuous, differentiable to non-differentiable, which make it difficult to adjust inputs for an optimum process [38]. In general, three principal groups, including analytical, experimental, and Artificial Intelligence (AI) models, have been used to study the behavior of LBM. Analytical methods include three subdivisions, i.e., numerical, stochastic, and exact methods [36]. Among these methods, numerical approaches like finite element method and finite difference method have been vastly applied to evaluate the behavior of LBM in various conditions. Design of Experiments (DOE) methods such as response surface method and Taguchi method are beneficial to extract accurate mathematical models by implementing limited experiments. The experimental data are used to formulate the relationships between quality features and input parameters by curve fitting methods. Recently, AI methods came to the attention of the researchers due to the progress in computing systems and their advantages [1,39]. Many studies have been conducted to model and optimize the behavior of the LBM process using one or several of these methods [40–42].

Artificial Intelligence (AI) is the most current technology that is composed of biological-based methodologies, including artificial neural network (ANN), fuzzy logic (FL), metaheuristic algorithms, as well as hybrid techniques and has attracted growing attention worldwide [43,44]. AI, like the human, has the capabilities of learning, reasoning,

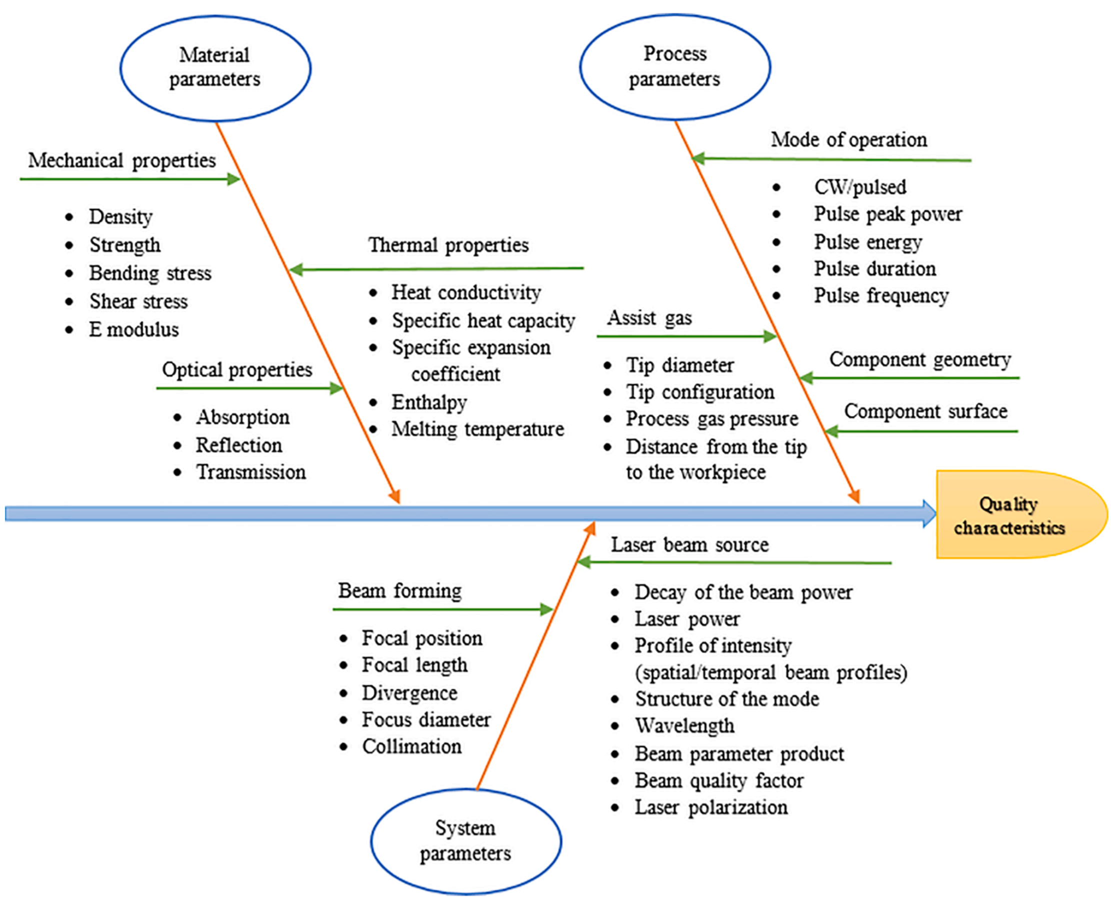


Fig. 4. The effective parameters on the LBM process.

Table 1
The effect of process parameters on cutting performance in metals [63].

Process parameter	Cut performance	
	Too high	Too low
Laser power	Kerf increase; Recast and dross increase; Wavy straions.	Kerf decreases; Loss of cut.
Cutting speed	Kerf decreases; Loss of cut increased surface roughness; Wavy striations.	Kerf increases; Recast and dross increase; Increased taper.
Focus position	Kerf increases; Recast and dross increase; Deep striations; Loss of cut.	Kerf increases; Recast and dross increase; Loss of cut.
Assist gas pressure	Prominent striations; Erosion at bottom of cut; Excessive burning.	Dross, Inadequate ejection; Partly closed kerf.
Standoff distance	Dross.	Prominent striations.
Nozzle diameter	Dross and high gas consumption.	Centering critical; Inadequate ejection; Partly closed kerf.

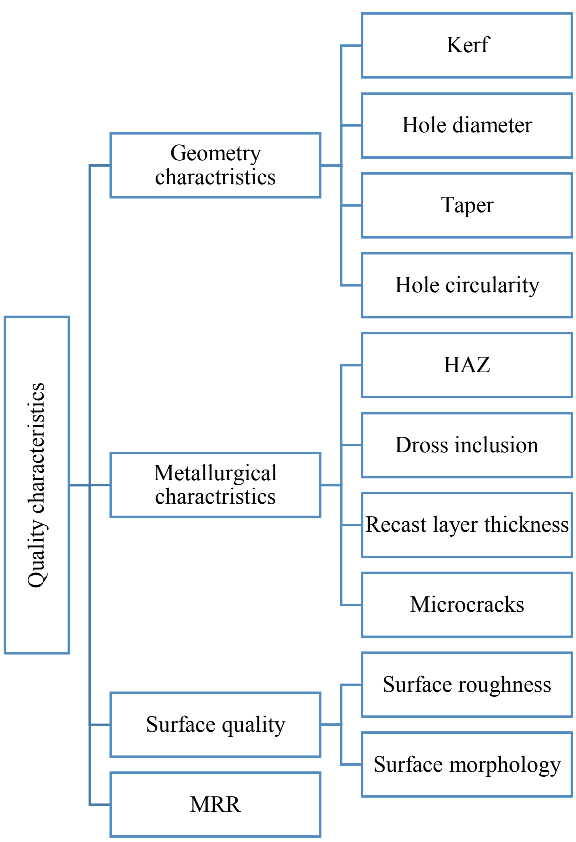


Fig. 5. The quality characteristics of LBM.

communication, perception, and decision making. AI has a remarkable performance in computer-integrated engineering applications [45,46]. For example, improvement in monitoring and efficiency of production processes as well as auto-correction are some applications of AI in manufacturing [47]. In the case of laser material processing, AI can be effectively applied for controlling and choosing optimal process parameters for achieving the suitable quality characteristics that may not be obtained using traditional methods [48,49]. The progress in the development of AI techniques has enabled their applications in modeling and optimization of various laser material processes such as laser welding, laser machining etc. [38,50]. In addition, some recent AI techniques like deep learning approaches have been employed in classification, monitoring and defect detections of the laser material processes [51–53]. The stunning capability of the deep learning methods has great potential to obtain better features of the LBM process [54].

This review aims to focus on the AI techniques applied for modeling and optimizing quality characteristics in LBM. The studied quality characteristics include geometry characteristics, surface quality, metallurgical properties, and material removal rate (MRR). The flow of the contents in this review is shown in Fig. 2. In the first section, while the introduction of the principle of the LBM process, various effective parameters and quality characteristics of the process are discussed. In the second section, the principles of the most applied AI techniques in LBM are proposed with respect to the advantages and limitations. Finally, a guideline is provided to choose the right AI algorithm for a specific problem, which allows researchers to consider the best-fit approach. Furthermore, the opportunities available are also discussed. In the meantime, the present review may be used as a guide for the applications of AI in LBM.

2. Laser beam machining

Nowadays, LBM, as an efficient alternative for certain conventional machining processes, has attracted the attention of researchers to conduct vast experimental and numerical studies. LBM process has a broad range of machining capabilities, including machining different materials such as metal and non-metallic with different properties (soft, hard, ductile to the brittle transition temperature, highly conductive, and thermally sensitive) [55]. Being a non-contact machining process, LBM does not have tool deflections, cutting forces, vibrations of the machine, and tool wear [7,8].

LBM has been used as a valuable tool for cutting, grooving, turning, milling, and drilling. The schematic of laser beam cutting as one of the primary Laser beam cutting configurations is shown in Fig. 3. In LBM as a thermal process, the laser beam is focused on the surface of the material, raising its temperature rapidly above the melting point and causing fast evaporation. Percussion and trepanning are the two prime types of laser beam drilling. In percussion laser beam drilling, the laser beam does not move during material removal, while trepanning laser beam drilling includes movement of the laser beam over the hole circumference [56]. Typically, a high-pressure gas jet called assist gas is used to blow the molten material away in LBM [57].

It is complicated to model the LBM due to many parameters that influence the performance of the process [58,59]. The impact of various LBM parameters on quality characteristics was examined carefully by many researchers [60–62]. Generally, the significant parameters in LBM can be categorized into three main types, namely laser parameters, material parameters, and process parameters [8]. It has been shown that the LBM parameters such as laser power, cutting speed, pulse width, assist gas pressure have a considerable effect on quality characteristics of laser machined workpiece [36]. The effective parameters on LBM are shown in Fig. 4.

Setting adequate parameters in LBM plays a crucial role in a high-performance process. When the parameters are set too low or too high, the impacts of the process parameters on the laser cutting performance cause inefficiency in the process [3]. The difference between the effects of high-level and low-level process parameters on the cut quality is provided in Table 1. Many researchers have evaluated the impact of the setting parameters on quality characteristics of LBM [58], which include surface quality, metallurgical properties, the geometry of machined workpiece, and material removal rate (MRR), as shown in Fig. 5.

3. Artificial intelligence

Nowadays, AI has attracted considerable attention as an advanced tool for solving complex practical problems in different areas [64,65]. In a general sense, AI is defined as the ability of computers and the other

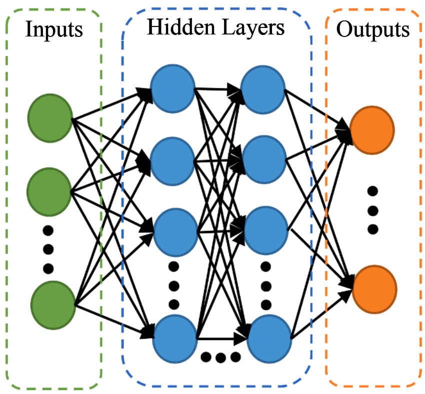


Fig. 6. A schematic of an ANN.

machines to imitate the smart behavior of humans and nature for solving practical problems. In general, two fundamental concepts, including learning and reasoning in modeling and optimizing by utilizing AI, are used. Learning and reasoning are used to construct models automatically and draw a logical conclusion based on the accurate recording of facts and observations, respectively [66,67]. A well-established AI method can be successfully applied for a broad range of systems. It can be used for simultaneous modeling and optimizing a variety of features, which is not possible using conventional approaches [68]. AI includes a number of branches, i.e., artificial neural networks (ANN), fuzzy logic (FL), metaheuristic optimization algorithms, and hybrid methods, which are briefly described in the following.

In general, the development process of AI models can be divided into five main steps, including data selection, normalization, data division, hyperparameters selection, and evaluation [69]. In the first step, inputs and outputs parameters should be selected based on the related problem. A comprehensive model can be obtained by considering all of the effective parameters on the outputs. After data selection, the data should be prepared for training the model. In this step, the inputs and outputs data are normalized into [0,1] or [−1,1]. Usually, normalization can enhance the performance of AI models. The collected data should be split into training and testing data sets, which are used for checking the accuracy and generalization of the model. The next step is to select the hyperparameters of the model by trial and error or using optimization methods (Section 3.4.2). Choosing appropriate hyperparameters has a vital role in the training of AI models. The final step is to evaluate the performance of the model by calculating the error in the prediction of outputs. The smaller difference between errors in training data and testing data indicate the more superior generalization of the model.

3.1. Artificial neural network

One of the most well-known and applicable AI algorithms is ANN that transfers the rule or the knowledge behind the empirical data to the network structure [70]. ANN can be used in different configurations for different applications, including pattern recognition, data extraction, classification, prediction, and process modeling [46]. This method derives the solution of the non-linear and complicated modeling by simulating the network of human brain neurons [71].

An ANN composes of several layers in which neurons place in them. A general structure of an ANN is shown in Fig. 6. As can be seen, a network is composed of three main layers where the neurons of the input layer determine the independent input variables, and the neurons of the output layers define the independent output variables. By proper selection of the number of neurons in each layer and the number of hidden layers, an acceptable model can be established [72]. For this purpose, a trial and error method or the optimization techniques are used. In the ANN structure, every neuron is connected with the other neurons with specific weights. In each hidden layer, the input is received by each neuron, and after processing, the neuron produces an output signal (weight) via net function and activation function.

There are three main learning methods of training ANN: supervised learning, unsupervised learning, and reinforcement learning. These methods can also be employed to train other AI techniques. In supervised learning, the network weights are modified so that the variation between the output (predicted) values and the target (actual) values is minimized [73]. This process iterates until the prediction error falls in an acceptable error range. In fact, the final weights of the network are obtained in this way. Generally, the neural network learned by this method can ideally be used for classification and prediction. While unsupervised or self-supervised learning is usually great for clustering operation [68]. In this learning technique, the network operation is checked internally, and the weights of the network are adjusted without external influence. A method between supervised and unsupervised learning methods is reinforcement learning. In this method, by receiving the environmental feedback without any detailed information about the output and input data, the network determines whether the action has been desired or undesired [74]. On this basis, the parameters of the network are adjusted.

3.2. Fuzzy logic

The fuzzy set theory is a mathematical template to formulate and

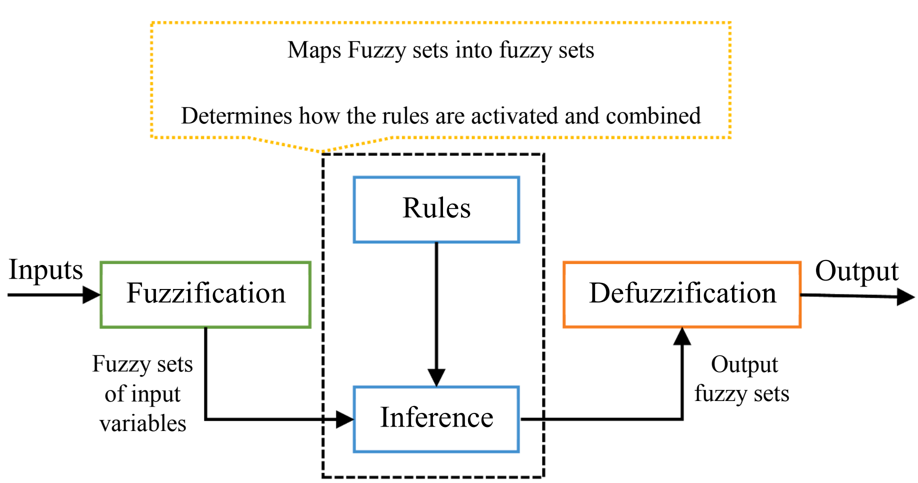


Fig. 7. Fuzzy inference system (FIS) architecture.

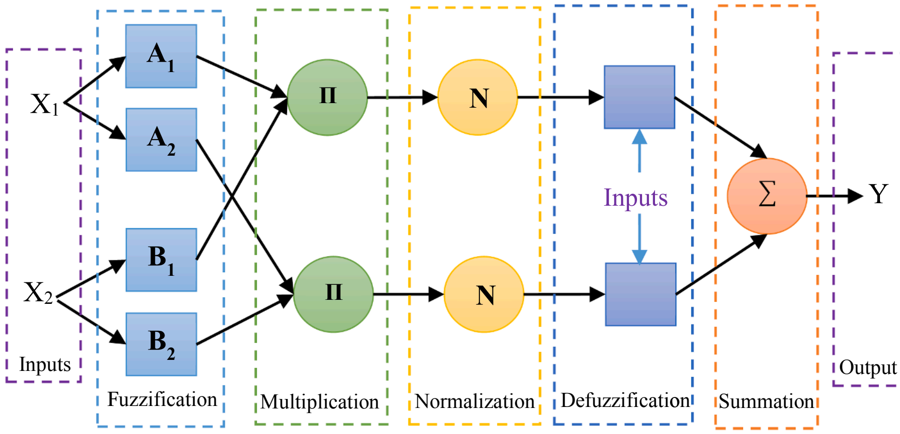


Fig. 8. Schematic of an ANFIS.

analyze these features and concepts [75]. This theory is a natural development and extension of the ordinary set theory, which is consistent with the natural concept and language of humans. In the field of the regular set theory, every set defines with a feature. If the considered object has that feature, it is a member of the corresponding set, and if not, the object is not a member of that set.

A fuzzy set is a set in which the membership degree of its members is steadily selected from the interval [0,1] [76]. This set is defined uniquely and entirely by the membership function $\varphi_A(z)$, which can be considered as the acceptance degree of the Z set as a member of A set. The closeness of the value of the membership function to one indicates the more belonging to the fuzzy set, and its closeness to the zero indicates the less belonging to the fuzzy set.

A fuzzy logic system is defined based on the if-then rules, where these rules are acquired from various sources such as knowledge, experiences, feelings, inspiration from nature, and human consciousness [77]. A

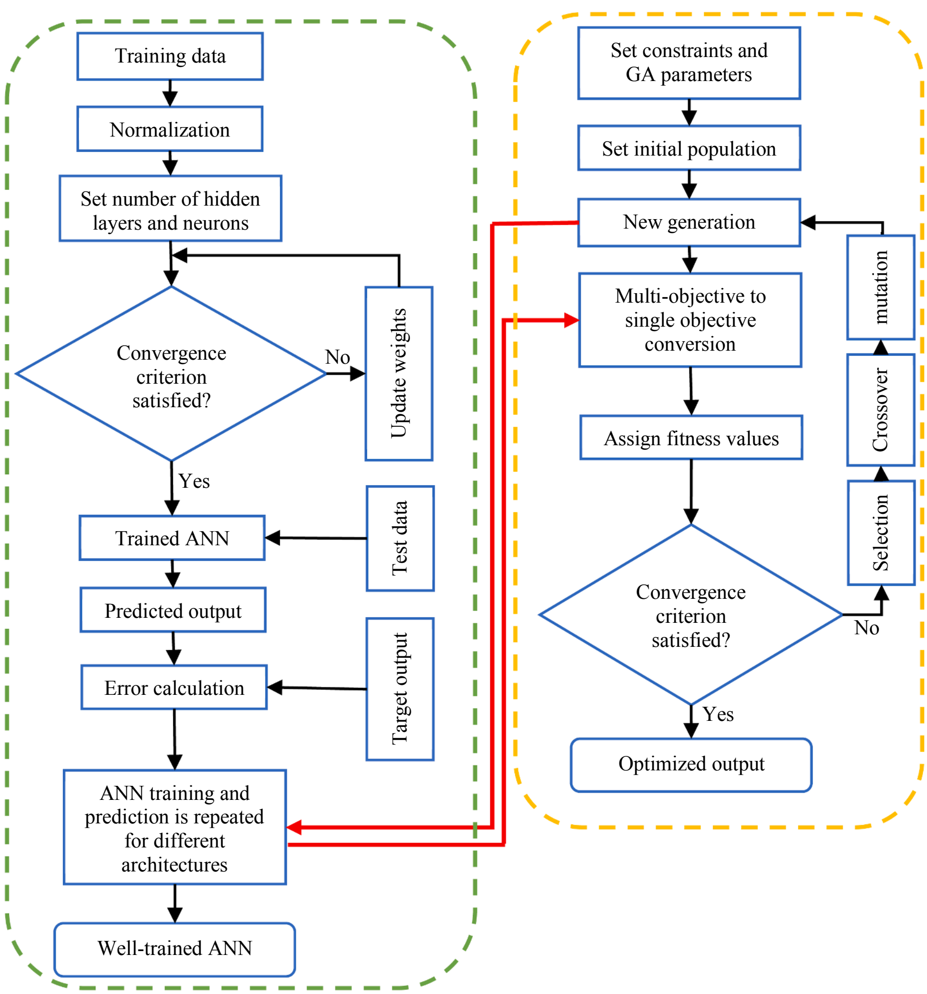


Fig. 9. The flowchart of integrated GA and ANN.

Table 2
Review of AI techniques for prediction and optimization of geometry characteristics in LBM.

Type of AI techniques	Type of LBM	Material of workpiece	Inputs	Outputs	Remarks	Authors [Reference/ Year]
ANN Multi-objective optimization (PSO)	Nd:YAGlaser cutting	AA1200 aluminum alloy sheet	Cutting speed; Pulse energy; Pulse width;	Kerf deviation; Kerf width; Surface roughness; MRR;	Reduction of kerf width, kerf deviation, and surface roughness values by 36.75%, 26.25%, and 14.94%, respectively, and increase in MRR by 24.67%.	Chaki et al. [98/2020]
ANN GA PSO	Nd:YAG laser cutting	Inconel-718	Assist gas pressure; Standoff distance; Cutting speed; Laser power;	Top kerf width; Bottom kerf width; Kerf taper;	Obtaining the optimal cutting parameters for the better quality cut with high precision and geometrical accuracy.	Shirvastava et al. [99/ 2019]
ANN	Nd:YAG laser cutting	Basalt and glass layered hybrid composite	Lamp current; Pulse frequency; Cutting speed; Pulse width; Assist gas pressure;	Kerf deviation;	Obtain well correlation between the predicted and experimental values.	Jain et al. [100/2019]
TaguchiANN	CO_2 laser cutting	Steel ST-37	Laser power; Cutting speed; Focus position; Assist gas pressure.	Kerf width on the top; Kerf taper;	Reduction in kerf width on the top and kerf taper.	Alizadeh et al. [40/2019]
Multi-objective optimization (GA)	Nd:YAGlaser cutting	Inconel-718	Assist gas pressure; Standoff distance; Cutting speed; Laser power.	Kerf deviation; Kerf width; Kerf tape;	Improvement of 88%, 10.63% and 42.15% in kerf deviation, kerf width and kerf taper, respectively.	Shrivastava et al. [101/ 2018]
Multi-objective optimization (PSO)	Nd:YAGlaser cutting	Inconel-718	Assist gas pressure; Standoff distance; Cutting speed; Laser power;	Kerf width; Kerf taper;	Improvement in kerf width and kerf taper are about 10% and 57%, respectively.	Shrivastava et al. [102/ 2018]
Multi-objective optimization (GA)	Nd:YAGlaser cutting	Titanium alloy	Assist gas pressure; Pulse width/Pulse frequency; Cutting speed;	Kerf width; Kerf deviation;	Improvement of 29.78% for kerf width and 95% for kerf deviation.	Kumar et al. [103/2018]
ANN Fuzzy logic	CO2 laser cutting	AISI 304 stainless steel	Laser power; Cutting speed; Assist gas pressure; Focus position;	Kerf width;	The mean absolute percentage errors; Fuzzy logic = 3.83% ANN = 5.79%.	Madic et al. [104/2016]
Fuzzy logic	CO_2 laser cutting	PMMA	Assisted gas pressure; Laser power; Cutting speed; Standoff distance;	Kerf width;	Relative error and fit goodnesses are 3.852% and 0.994, respectively.	Hossain et al. [79/2016]
ANN GA	Nd:YAG laser cutting	AA1200 aluminum alloy	cutting speed pulse energy pulse width	Kerf width Kerf deviation	kerf width and kerf deviation with mean absolute % error of 0.42% and 1.05% for modeling and optimization results in absolute % error of 1.87% and 2.00% for optimization	Chaki et al. [93/2012]
Fuzzy logic Multi-objective optimization	Nd:YAG laser cutting	Duralumin	Assist gas pressure; Pulse width/Pulse duration; Pulse frequency; cutting speed;	Kerf width; Kerf deviations at top and bottom sides;	The optimum parameter values for minimization of the kerf width and kerf deviation at top and bottom sides.	Pandey et al. [105/2011]
ELM ANN	Fiber laser drilling	Ti-6AI-4V alloys	Laser power; Assist gas pressure; Cutting speed;	Hole diameter; Taper angle; Spatter forming area;	The estimation accuracy of the ELM (R = 0.99995) model is higher than ANN (R = 0.99985) model.	Ay [106/ 2018]
DOE ANN	Yb:KGW femtosecond laser micro-drilling	Stainless St-303	Pulse frequency; Pulse width; Laser power;	Hole roundness; Hole taper; Variation in hole entrance diameter; Recast layer; micro-cracks;	Mean Absolute Percentage Error (MAPE) is 8%.	Casalino et al. [107/2017]
GA	Nd:YAG laser trepan drilling	Inconel-718	Assist gas pressure; Current; Stand of distance; Cutting speed;	Hole diameter;	The optimum value of hole diameter at the optimum setting has found equal to 1.232 mm.	Dhaker et al. [108/2017]
RSM ANN GA Hybrid model	Nd:YAG laser micro-grooving	Aluminum oxide (Al2O3) ceramic	Assist gas pressure; Lamp current; Pulse frequency; Pulse width; Cutting speed;	Upper width; Lower width; Depth;	The minimum deviation of upper width, lower width, and depth are −0.0278 mm, 0.0102 mm and −0.0308 mm, respectively.	Dixit et al. [109/2019]
RSM ANN GA Hybrid model	Nd:YAG laser micro-grooving	Aluminum oxide (Al2O3) ceramic	Assist gas pressure; Lamp current; Pulse frequency; Pulse width; Cutting speed;	Upper width; Lower width; Depth;	Mean square error = 0.000099; Obtaining optimum laser micro-grooving process parameters.	Dhupal et al. [110/2018]
Fuzzy logic FEM	Laser grooving	Ceramic	Laser speed; Laser power;	Groove depth;	The goodness of fit was found to be 0.991, and the mean relative error was 4.714%.	Parandoush et al. [111/ 2015]

(continued on next page)

Table 2 (*continued*)

Type of AI techniques	Type of LBM	Material of workpiece	Inputs	Outputs	Remarks	Authors [Reference/ Year]
RSM ANN multi-objective genetic algorithm (GA)	Nd:YAG laser micro-grooving	aluminum oxide (Al2O3)	lamp current Pulse frequency Pulse width Cutting speed Assist gas pressure	Upper width; Lower width; Depth;	Predicted minimum deviation of upper width, lower width and depth are −0.0101, 0.0098 and −0.0069 mm, respectively.	Dhupal et al. [112/2009]
Multi-objective optimization (GA)	Nd:YAG laser drilling	Titanium	Gas pressure; Pulse width; Pulse frequency; Trepanning speed;	Hole taper; Circularity;	Improvements of 49% and 8% have been registered in hole taper and circularity, respectively.	Goyal et al. [113/2016]
ANN GA	Nd:YAG laser drilling	Nickel-based super alloy Nimonic 263	Pulse frequency; Pulse duration;	Entry-side hole diameter; Exit-side hole diameter; The circularity of entry-side hole; The circularity of exit-side hole; Aspect ratio; Taper; Spatter;	the actual optimal parameter settings that yield the maximal synthetic performance measure	Sibalija et al. [114/2011]
ANN GA	Nd:YAG laser drilling	Stainless steel 304	Peak power; Pulse time; Pulse frequency; Number of pulses; Gas pressure; Focal plane; position	Hole entrance diameter; The circularity of entrance and exit holes; Hole exit diameter; The taper angle of the hole	the effect of input parameters on each output parameter was investigated in a single criterion optimization case.	Ghoreishi et al. [115/ 2007]

straightforward form of the if-then rule can be defined as the following:

$$\text{If } x \text{ is } A \text{ then } y \text{ is } B \tag{1}$$

where A and B are the linguistic rules which are defined by fuzzy logic in the x and y domains, respectively. This form of fuzzy logic reasoning enables one to express the problem with the human language and receives the fuzzy answers to them [45].

In the fuzzy set theory, the fuzzy inference system (FIS) is used to map the inputs on the outputs. Fig. 7 displays a schematic of the regular FIS structure. Generally, the basic structure of FIS composes of three conceptual parts. The first parts are rules, including a selection of fuzzy rules. The second part is a database where the membership rules are used in the fuzzy rules defined in its format. Finally, the third part is the inference mechanism by which the inference procedure is accomplished with the help of existing facts and rules to achieve a reasonable output [78]. The two most common and applicable FIS are Mamdani and Takagi-Suen-Kang (TSK). The difference between these systems lies in the fuzzy rules and procedure of calculating sum and defuzzification in them [79].

3.3. Metaheuristic optimization

Generally, most of the traditional optimization algorithms have been defined based on the partial deferential concept of multivariable functions [74]. In these methods, performing the optimization algorithm on the specific points on the domain of the target function, as well as the linear motion between these points will cause the method to be converged toward the local optimum of the target function. This issue will be intensified in a case where the target function has severe fluctuations. Recent studies have proposed several metaheuristic optimization methods for optimizing conditional functions to overcome these issues [80]. These optimization techniques, like the other AI methods, are inspired by nature. The most critical capabilities of these methods include easy implementation, reduction of the search space, and finding an overall optimal search space with the possibility close to one [81]. In the present study, the two most applicable metaheuristic methods, i.e., genetic algorithm (GA) and particle swarm optimization (PSO) have been investigated.

3.3.1. Genetic algorithm

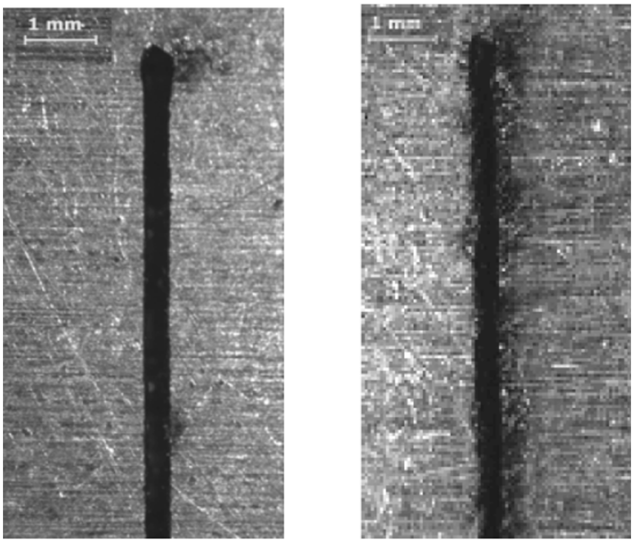
GA is a concept of Darwin's theory and the genetic science of evolution [82]. This algorithm is according to the survival of the natural or fittest selection [83]. GA is a useful tool for image perception, feature selection, pattern recognition, and machine learning [84]. GA can be considered as a directional random optimization method that moves toward the optimal point gradually. By comparison of the GA's features with the other optimization methods, it can be found that GA is applicable for all problems without having any information about the problem and without applying any limitation on the type of its variables. GA also has the proven efficiency in finding the overall optimum and enables solving the complex optimization problems where the classical methods are either not applicable or not reliable in finding the general optimum [85].

In GA, one population of people will survive in the environment based on their merits. People with better capabilities have more chance to marry and reproduce. Therefore, after some generations, children with better efficiency will survive. The chromosomes are evaluated in each generation, and they will be survived and reproduced proportional to their values. The reproduction is driven by mutation and crossover operators. The superior parents will be selected based on the fitness function. In each step of GA run, one bunch of search space points undergo the random processing, so that a sequence of characters is attributed to each point, and on each of these sequences, the genetic operators apply [86]. Then the resulted sequence is decoded in order to obtain the new points in the search space. Eventually, according to the value of the target function at that point, the probability of their participation in the next stage is determined [87].

3.3.2. Partial swarm optimization

Recently, a group of optimization algorithms has been proposed based on the social interaction simulation of a special group of living things in order to achieve food resources. The partial swarm optimization algorithm that was developed in 1995 by Kennedy and Eberhart falls in this group [88,89]. This optimization algorithm inspired from the way of living of the birds which live together and satisfy their needs, including food searching collectively and with the help of each other and by using collective wisdom. In this algorithm, it has been assumed that the birds searching for food sense their distance to the food instinctively while having no information about its location. Furthermore, it has been assumed that all birds know their nearest location of the bird to the food by sharing their information and adjust their position in the search space on this basis.

In PSO, every reply to the problem is considered as a bird, which in the research space is named a particle. Each particle has the fitness value, which is obtained from the fitness function of the problem. On this basis, the closer the birds to the food source are, the higher their fitness values are. Also, each bird has a velocity vector that indicates the



(a) (b)

Fig. 10. Microscopic display of kerf acquired (a) with optimal parameter and (b) with initial parameter [70].

motion's direction and the velocity of the bird. In the optimization process, each bird modifies itself based on the cognition and social experience.

PSO is a very robust algorithm among the other similar algorithms and can efficiently work with continuous and discontinuous variables. PSO is more effective than the other identical optimization techniques and needs less function calling to achieve the better or the same results of the other similar methods. Another advantage of PSO is the easy computer implementation, which can coincide with the constraints and variables in a particular state.

3.4. Hybrid

3.4.1. Adaptive neuro-fuzzy inference system

ANFIS is a combined AI method that was developed in 1993 by Jang for solving the complicated and non-linear problems [90]. There are two main branches of AI in ANFIS: the ANN and FL, where both models are combined to take advantage of their capabilities [91]. ANFIS has obtained its learning capability from the ANN and also its logic capability from the FL.

Fig. 8 shows the scheme of the ANFIS. As can be seen, ANFIS composes of five main parts, including fuzzification, multiplication, normalization, defuzzification, and summation. The main structure of an ANFIS relies on a model by which the input specification, the input membership function, the rule, the output specifications, as well as the output membership function are mapped into the input membership functions, some specific rules, a set of output specifications, output membership functions as well as single-value output, respectively.

With the use of a set of input and output data, ANFIS is capable of creating a fuzzy system wherein the input and output membership functions can be adjusted well using the back-propagation algorithm or a mixture of the least-squares approach and the back-propagation algorithm.

3.4.2. Combination of modeling and optimization methods

Recently, modeling techniques are increasingly being integrated with metaheuristic methods such as GA and PSO for optimization developments in engineering [92]. By the development of the hybrid method, the closed-form objective function is no longer needed. It means that the objective function is internally calculated by combining the modeling and optimization techniques. It can be more useful when there is no theoretical relation between output and input variables [93]. A logical flow diagram of a hybrid GA-ANN model is shown in Fig. 9. As can be seen in the flowchart, the output of ANN is used as an objective function in GA.

In addition, optimization methods can also be used for obtaining the optimal values of hyperparameters of AI models. The values of hyperparameters have a noteworthy effect on the performance of the model in prediction. These parameters are chosen before training the models [94]. For instance, the number of hidden layers and neurons are two main parameters in ANN configuration [95]. Selection optimal value of these parameters is required to achieve an efficient and fast model.

4. Application of AI in laser beam machining

LBM is one of the advanced machining techniques by which high-quality cuts with high efficiency can be achieved by control of different process parameters and their interactions. The quality characteristics of LBM depend heavily on the input parameters [96]. Developing a highly accurate functional relation between output and input variables in the LBM process is of great importance to tackling -challenges induced by the dynamic nature of LBM [97]. This non-linear and complex behavior in the LBM process can be modeled by applying AI techniques. The geometry characteristics, metallurgical characteristics, material removal rate (MRR), and surface quality are considered as the quality characteristics of a laser machined workpiece. This section includes a review of works conducted on the application of AI in optimizing and modeling of different attributes involved in LBM quality characteristics.

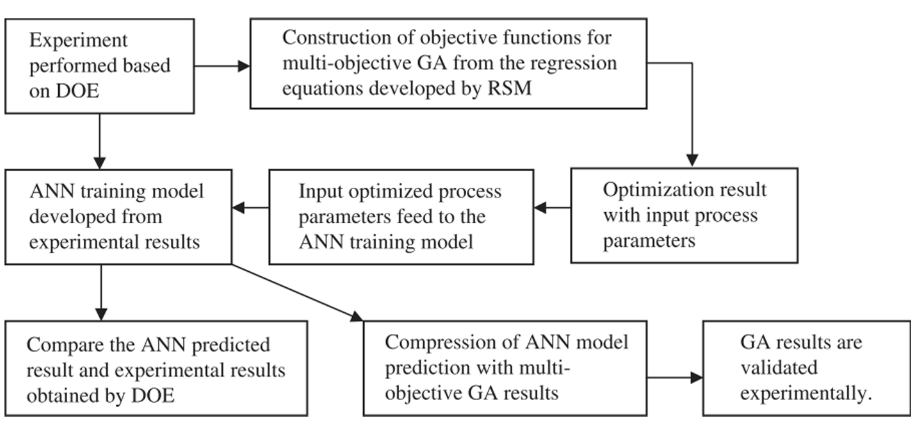


Fig. 11. The methodology of RSM–ANN–GA approach [89].

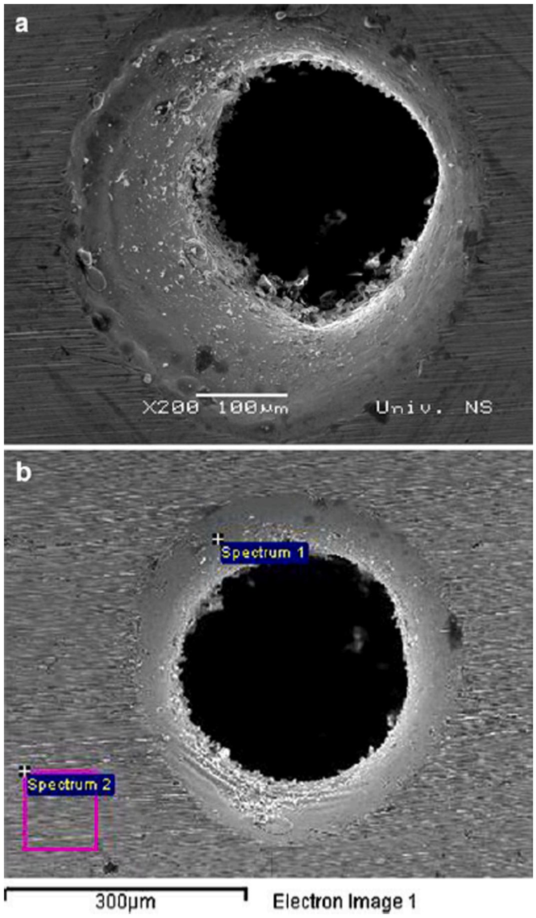


Fig. 12. Entry-side hole drilled a) with initial parameters setting, and b) with optimized parameters setting [114].

4.1. Geometry characteristics

Kerf is a gap width of the cut that is removed by LBM. Small kerf width is one of the main requirements of a good quality cut. It is obvious that obtaining a kerf width with the minimum value is necessary in engineering applications [55]. To this end, several researchers tried to develop an AI algorithm for kerf width prediction and optimization in LBM. The list of conducted studies on the applications of AI in geometry characteristics of a laser machined workpiece is provided in Table 2.

ANN, as the most common AI technique, has been frequently applied in the prediction of kerf characteristics of a laser machined workpiece. In a study, Jain et al. [100] applied the ANN for proposing a validated mathematical model of kerf deviation in laser machining of a basalt-glass hybrid composite. Madic et al. [104] compared the performance of ANN and FL to model kerf width. They found that the prediction capability of the FL model is better than ANN, while the ANN model shows better generalization. In work implemented by Chaki et al. [93], the ANN model is capable of predicting the kerf deviation and kerf width with mean absolute errors (MAE) of 1.05% and 0.42%, respectively. By using a hybrid method, the trained ANN model is also used to calculate the objective function value for GA optimization. In another study, two quality features of kerf taper and kerf width in the CO_2 laser cutting process were investigated with respect to the four influential parameters, including assist gas pressure, focus position, laser power, and cutting speed [40]. Consequently, a significant improvement in kerf quality was achieved by applying an AI-based hybrid approach through the optimal set of parameters (Fig. 10). Similarly, a substantial decrease in kerf deviations at the top and bottom sides has been obtained by a combination of ANFIS and multi-objective optimization [105].

The metaheuristic optimization algorithms are also successfully applied to achieve the best setting for a good quality kerf. Kumar et al. [103], applied GA for the multi-objective optimization of kerf width and kerf deviation in Nd:YAG laser cutting of Titanium alloy. Based on their findings, the optimal values of kerf deviation and kerf width were improved by about 95% and 29.78%, respectively, with the total improvement of 27.39% comparing to the initial parameters setting. Shrivastava et al. [99,101,102] used multi-objective optimization, including GA and PSO, to obtain the optimal value of different process parameters for improvement of kerf deviation, kerf width and kerf taper in the Nd:YAG laser machining of Inconel-718.

The function approximation capability of ANN and quality characteristic optimization capability of GA in the LBM process have gained significant attention from researchers [110,111]. In the case of integrating the ANN model with the GA, this hybrid model can be efficiently used to determine the optimal parameters for the laser micro-grooving process for which a significant improvement can be obtained by optimal parameter settings [109,110,112]. It is believed that the multiple approaches, including experimental, evolutionary, statistical, and stochastic, provide effective methodologies for the improvement of the laser micro-grooving process. They can be used in real-time process monitoring, model predictive control process, and optimization in a number of machining processes [110,116]. Dhupal et al. [112] have performed a work to minimize the deviation of lower/upper widths and depth of laser turned micro-grooves using a multiple hybrid approach (Fig. 11). As shown in Fig. 11, design of experiments (DOE) was conducted for laser operations, and then the outputs of DOE in different process parameters were used to develop the ANN model, and finally, the trained ANN was combined with multi-objective GA optimization for obtaining the minimum deviation. In another multiple approach methodology, Parandoush et al. [111] concluded that the finite element method (FEM) accuracy could be enhanced effectively using a FL without taking into account the multiple reflection phenomena for calculation.

Laser drilling as an efficient process to fabricate precise holes has gained a vast attraction among manufacturers. Applications of AI techniques can considerably enhance the features of this process. Casalino et al. [107], applied the ANN model to offer a reliable understanding of the best conditions for various quality characteristics such as geometric characteristics (hole taper and variation in hole entrance diameter, hole roundness) and metallurgical characteristics (micro-cracks and recast layer) of Yb:KGW laser drilled micro holes. The hole taper and circularity of the Nd:YAG laser-drilled workpiece have been optimized in terms of pulse width, assist gas pressure, trepanning speed, and pulse frequency by Goyal et al. [113]. By selecting optimal process parameters, an enhancement of 49% in hole taper and 8% in circularity have been established. In work performed by Ay et al. [106], to predict the features that specify the hole quality in the Ti-6Al-4V alloy drilled by a fiber laser, two models have been established by the use of ANN and extreme learning machine (ELM).

The capability of AI techniques in adjusting the process parameters in single or multi-objective optimization modes of the laser percussion drilling process was indicated by Ghoreishi et al. [115]. In this research, the different states of hole entrance diameter, hole entrance circularity, hole exit circularity, and taper angle were singularly and simultaneously optimized by using the combination of ANN and GA. Dhakera et al. [108] in a study have examined four essential process parameters, including laser current, trepanning speed, standoff distance, and assist gas pressure to determine an optimal hole diameter by applying the GA technique. Their results indicated that the smallest hole diameter was produced at the minimum current and the maximum cutting speed, standoff distance, and gas pressure in the studied range. In a comprehensive study [114], several quality characteristics of a pulsed Nd:YAG laser drilling, including taper, spatter, aspect ratio, the circularity of entry-side hole, the circularity of exit-side hole, entry-side hole diameter, and exit-side hole diameter were simultaneously optimized by

Table 3
Review of AI techniques for prediction and optimization of metallurgical characteristics in LBM.

Type of AI techniques	Type of LBM	Material of workpiece	Inputs	Outputs	Remarks	Authors [Reference/ Year]
ANN Multi-objective Optimization GA	Nd:YAG laser drilling	Basalt-glass hybrid composite	Lamp current; Pulse frequency; Assist gas pressure	HAZ; Hole circularity;	Achieve a better quality drill with higher accuracy and precision.	Jain et al. [117/2020]
ANN GA	CO_2 laser drilling	Glass Fiber Reinforced Plastic Composite	Laser power; Cutting Speed; Assist gas pressure	HAZ extent; Bearing strength;	Excellent agreement between the experimental data and predicted results.	Solati et al. [118/2019]
Gray relation analysis Fuzzy logic	Nd:YAG laser cutting	Duralumin	Lamp current; Pulse width; Pulse frequency; Cutting speed	Kerf taper; HAZ;	The application of the hybrid approach is capable of reducing the kerf taper and HAZ of laser cut kerf by 2.52% and 42.32%, respectively.	Joshi et al. [119/2018]
ANN GA Hybrid model	Fibre laser cutting	Glass Fiber Reinforced Plastic Composite	Laser power; Cutting speed; Gas pressure	HAZ;	RMSE = 0.0046 $R^2 = 0.9976$	Anicic et al. [120/2017]
ANN GA	CO_2 laser cutting	Ti-6Al-4V	laser power; Radiation time; Focal diameter	HAZ; Temperature distribution;	An excellent agreement between the experimental data and predicted results were observed.	Shahri et al. [95/2017]
ANN	Fibre laser cutting	Glass Fibre Reinforced Plastic Composites	Laser Power; Cutting Speed; Gas Pressure	HAZ;	Predicting HAZ with more than 97% of accuracy.	Patel et al. [121/2016]
ANFIS	Laser cutting	Glass Fiber Reinforced Plastic Composite	Laser power; Cutting speed; Gas pressure	HAZ;	Cutting speed and Gas pressure have the highest and the smallest influence on the HAZ, respectively.	Petkovic et al. [122/2016]
GA	Nd:YAG laser cutting	Duralumin	Gas pressure; Pulse width; Pulse frequency; Cutting speed	HAZ;	The quality of cut in the laser cutting has been improved by reducing the heat affected zone as 30.01% at optimum level settings.	Norkey et al. [123/2014]
FEM ANN Multi-objective Optimization	Nd:YAG laser drilling	Aluminum	Pulse width; Pulse frequency; Peak power; Thickness of work piece	Hole taper; Material removal rates; Extend of HAZ;	Reduction of hole taper by 67.5%, an increase of material removal rate by 605%, and reduction of the extent of HAZ by 3.24%.	Mishra et al. [124/2013]
FEM ANN Multi-objective Optimization	Nd:YAG laser drilling	Inconel-718	Pulse width; Pulse frequency; Peak power; Thickness of workpiece	Hole taper; Material removal rates; Extend of HAZ;	Reduction of hole taper by 32.1%, an increase of material removal rate by 28.9%, and reduction of the extent of HAZ by 4.5%.	Mishra et al. [125/2013]
ANFIS	Nd:YAG laser drilling	Inconel-718	Assist gas pressure; Laser current; Standoff distance; Drilling speed	Recast layer thickness	Prediction of recast layer thickness with average error less than 5%.	Dhaker et al. [126/2019]
Multi-objective Optimization	Nd:YAG laser drilling	Inconel-718	Gas pressure; Pulse width; Pulse frequency; Cutting speed	Recast layer thickness at entrance; Recast layer thickness at exit;	Minimization of 99.82% and 85.06% in the recast layer thickness at entrance and exit, respectively.	Kumar et al. [127/2013]
ANN Multi-objective optimization	Nd:YAG Laser grooving	Die-steel	Lamp current; Frequency; Pulse width ; Air pressure	Depth of groove recast layer;	Obtaining the maximum depth of groove with a minimum height of recast layer	Dhara et al. [128/2008]
FEM ANN	Fiber optic coupled laser line diode	Glass	Temperature; Glass thickness; Time; Cutting speed	Thermal stresses; Stress at the leading edge; Stress at the trailing edge	An increase of 67% prediction accuracy was achieved with ANN.	Bilal Kadri et al. [129/ 2015]

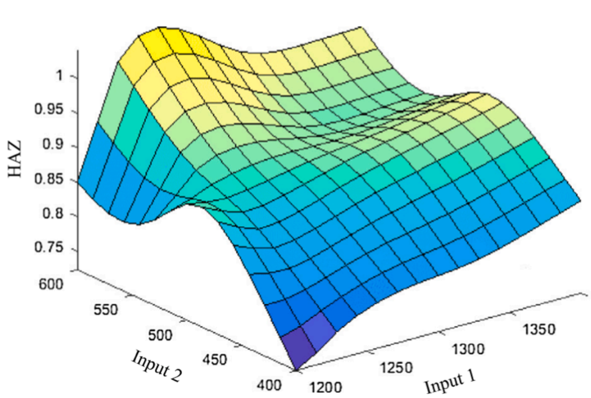


Fig. 13. The graph of the ANFIS model for predicting of the HAZ (mm), where input 1 is laser power (Watt) and input 2 is cutting speed (mm/min) [122].

using hybrid methods. The acceptable geometrical features of a hole that is established by an optimized laser drilling are shown in Fig. 12. It is demonstrated that the optimal value of the geometrical quality features of the laser machined workpiece can be achieved by setting proper process parameters.

4.2. Metallurgical characteristics

The highly localized heating creates the heat-affected-zone (HAZ) on the cutting surface in the LBM, which is limited to a narrow surrounding of the cutting zone. With the increase in the cut thickness and energy input per unit length, the HAZ width will be increased. The HAZ tends to cause mechanical and metallurgical defects such as residual stress, blue brittleness, and micro-cracks, etc. [95]. Generally, the HAZ is the main reason for alteration in metallurgical characteristics in the laser beam machined workpiece [36]. Therefore, it is necessary to decrease the HAZ as much as possible during LBM by the control of different factors. AI techniques can be adequately applied in LBM to achieve minimum HAZ. Applications of AI techniques used in the modeling and optimization of metallurgical characteristics of LBM are listed in Table 3.

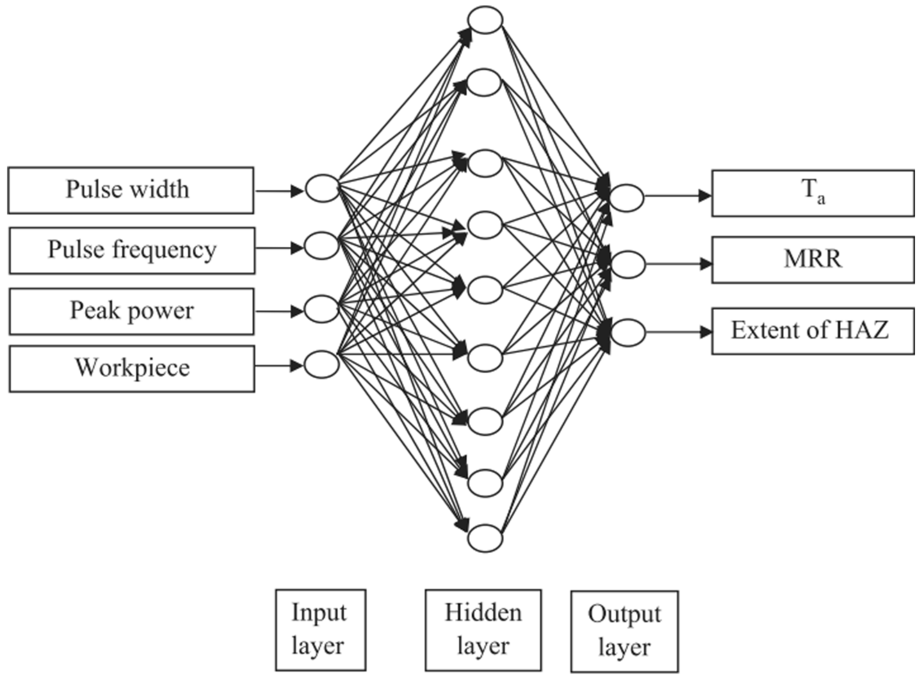


Fig. 14. Configuration of the applied ANN model [125].

Table 4
Review of AI techniques for prediction and optimization of surface qualities in LBM.

Type of AI techniques	Type of LBM	Material of workpiece	Inputs	Outputs	Remarks	Authors [Reference/ Year]
ANN	CO_2 laser cutting	AL6061T6 alloy	Cutting speed; Laser power; Sheet thickness; Assistant gas pressure;	Surface roughness; Cutting region temperature;	The mean values of error percentages between model outputs and experimental data are 5.79% and 0.66% for the surface roughness and the cutting temperature, respectively.	Yongbin et al. [134/2020]
ANN	CO_2 laser milling	PMM	Scan speed; Hatch distance;	Roughness; Depth;	The mean percentage error was 6.44%, 6.77%, and 3.41% for the depth, Ra and Rt, respectively.	Leone et al. [131/2019]
ANN ANFIS	fiber laser	201 steel	gas pressure, cutting speed and cutting seam width	laser cutting roughness	Average absolute error; ANN = 0.23 μm ANFIS = 0.08 μm	Zhang et al. [133/2017]
ANN	CO_2 laser milling	PMM	Time; Scan speed; Wave mode; Steep; Average power; Total released energy;	Roughness; Depth;	The Mean Absolute Percentage Error (MAPE) greater than 87% was obtained for all the parameters.	Addona et al. [135/2016]
ANN	CO_2 laser cutting	Tungsten alloy	Laser power; Cutting speed; Assist gas type;	Kerf width; Average surface roughness;	The average prediction error was found to be 5.5% for kerf width and 9.5% for surface roughness.	Klancnik et al. [136/2015]
ANN Optimization algorithm	CO_2 laser cutting	AISI 304 stainless steel	Laser power; Cutting speed; Assist gas pressure; Focus position;	Surface roughness;	The minimum surface roughness is obtained.	Madic et al. [132/2013]
Multi-objective PSO optimization	Nd:YAG laser milling	AISI H13 hardened tool steel	Scanning speed; Pulse intensity; Pulse frequency;	Depth; Width; Surface roughness;	the optimal parameters occur around a pulse frequency of 45 kHz and a scanning speed of 400 mm/min	Teixidor et al. [137/2013]
Multi-objective optimization GA	Nd:YAG laser cutting	Titanium alloy	Assist gas pressure, Pulse width/ Pulse duration; Pulse frequency; Cutting speed;	Kerf taper; Surface Roughness;	The optimum parameter values for different control factors are calculated.	Pandey et al. [57/2012]
Fuzzy logic	CO_2 laser cutting	Incoloy alloy 800	the power, assist gas pressure and cutting speed,	Surface roughness; Dross inclusion;	A good correlation is provided.	Zhian et al. [78/2011]
ANN Multi-objective optimization	Nd:YAG laser cutting	AISI H13 hardened tool steel	Pulse intensity; Scanning speed; Pulse frequency;	Surface roughness; dimensional quality;	minimum surface roughness and minimum volume error are obtained.	Ciurana et al. [33/2009]

The HAZ in the LBM process can be the consequence of various control parameters. Patel et al. [121] and Petkovic et al. [122] analyzed the effects of cutting speed, gas pressure, and laser power on HAZ in the laser cutting process. In their works, ANN and ANFIS models were used to choose the parameters with the greatest impact on HAZ. The results indicate that the gas pressure and cutting speed are responsible for the minimum and maximum influence of HAZ, respectively. Fig. 13 represents the ANFIS model for the prediction of HAZ via laser power and cutting speed (where input1 and input2 are laser power and cutting speed, respectively). Anicic et al. [120] proposed and compared three

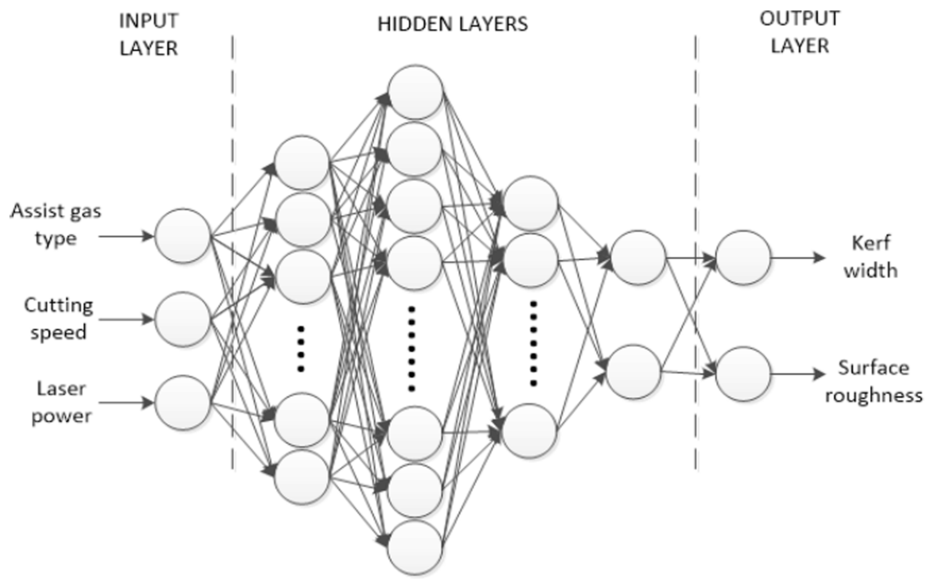


Fig. 15. The architecture of the ANN model for surface roughness and kerf width prediction [136].

predictive models to predict HAZ. They concluded that the ANN model, with about 97% accuracy for a specified range of input parameters, is a good option to predict HAZ.

Several studies have been implemented for modeling and optimization of HAZ in LBM by using Hybrid techniques. Norkey et al. [123] used the GA technique and second-order polynomial regression model to reduce HAZ and improve the quality of the cuts in the laser cutting of the duralumin sheet. Mishra et al. [124,125] applied the validated FEM-based thermal model of the laser drilling process to generate a sufficiently large number of data for a training ANN model. In Fig. 14, the configuration of the proposed ANN model has been shown. In addition, they applied a multi-objective optimization to produce a hole with good integral quality. In another work, by using a hybrid approach, Joshi et al. [119] decreased HAZ, and the kerf taper of the laser cut kerf by 42.32% and 2.52%, respectively.

In some studies, the GA technique was developed to solve the issues generated in the ANN technique. In fact, an integrated model of GA and ANN was developed to find the optimal architecture for ANN. For example, Solati et al. [118] examined the impact of key parameters involved in laser drilling on HAZ and bearing strength by applying the integrated GA-ANN model. They concluded that this integrated model is able to estimate HAZ, and bearing strength with high accuracy compared to the ANN model that its parameters are selected according to the trial and error approach. In another study, this integrated model was used to establish the relation between temperature distribution, HAZ, and process parameters [95]. Jain et al. [117] also modeled and optimized the values of HAZ and hole circularity in the drilling of a new hybrid composite by using the same method.

A residual molten material that does not vaporize or eject from the hole in the LBM is named the recast layer with features of high tensile

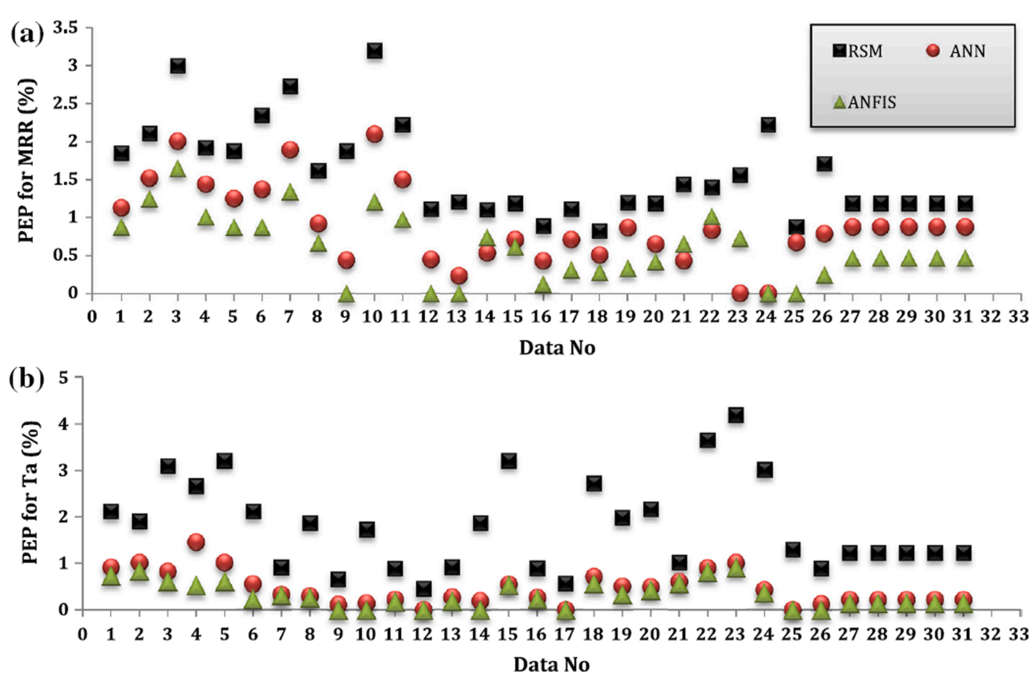


Fig. 16. The prediction error percentage (PEP) of RSM, ANN and ANFIS models in estimation of a) MRR, and b) Taper (Ta), in LBM of Al/Al2O3 metal matrix composite [144].

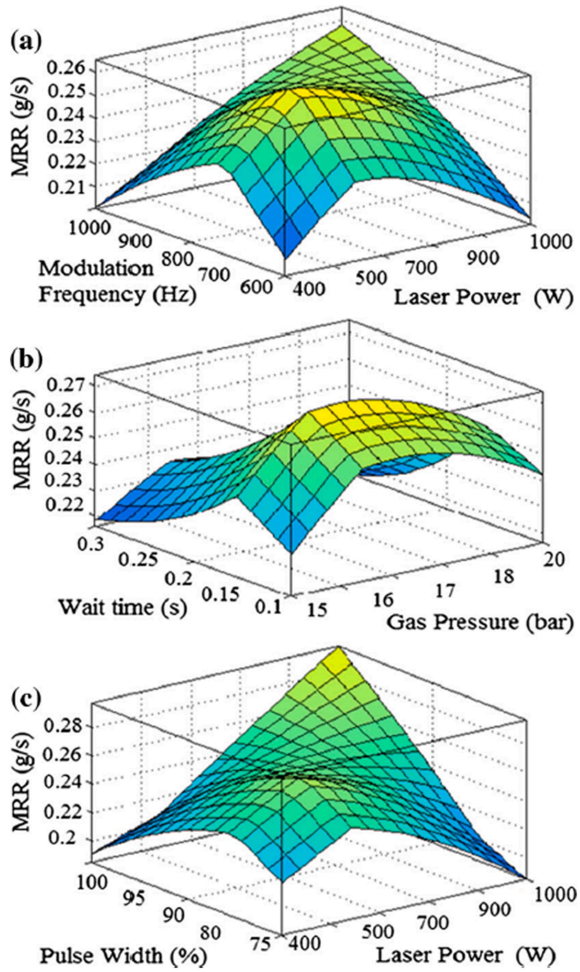


Fig. 17. The ANFIS model surface for MRR in terms of a) modulation frequency and laser power, b) wait time and gas pressure, and c) pulse width and laser power [144].

residual stresses, micro-segregated microstructure, and poor surface roughness. Dhaker et al. [126] successfully applied the ANFIS model to predict the recast layer thickness of the laser-drilled Inconel-718 sheet. It is observed that a lower drilling speed and more upper laser current produce a higher recast layer in the drilled hole. The recast layer often results in surface cracks [26]. Therefore, it is necessary to minimize the recast layer in LBM. Kumar et al. [127] used multi-objective GA optimization for simultaneously reducing the recast layer thickness (RLT) at entry and exit in laser drilling of a nickel-based superalloy substrate. The minimized RTLs were 99.82% and 85.06% at the entry and the exit, respectively. In a study performed by Dhara et al. [128], an optimal setting of the LBM parameters was predicted in order to obtain the minimum RTL with the maximum depth groove. In addition, a well-trained ANN model was used to generate a large number of predictions for better optimization. According to the results, the perfect parametric combinations can be obtained by applying the optimization technique that makes LBM practically efficient to use.

Thermal stress is applied to enforce the cracks in the laser thermal stress cleaving of brittle materials by the use of a controlled fracture approach, in which the material detaches along the cutting direction. However, this technique faces a challenge in the case of laser glass cutting, that is, the cut direction deviation at the trailing and leading edges in the glass sheets. Kadri et al. [129] applied the FEM and ANN methods to determine the stress fields at the trailing and leading edges in the glass sheets. They validated the predictions of both techniques with the experimental data and revealed that ANN has better performance than the FEM.

4.3. Surface quality

Surface quality is one of the significant cutting quality characteristics in LBM. Table 4 consolidates the applications of AI for predicting and optimizing the surface quality in LBM. In laser machining, the surface roughness formation has a sophisticated mechanism. This non-linear and complex behavior can be analyzed by applying AI techniques [130]. In other words, AI, as a powerful tool, can model and optimize the surface quality characteristics of the laser machined workpiece [131]. For instance, Madic et al. [132] considered four laser cutting parameters, including assist gas pressure, focus position, cutting speed, and laser power, to obtain an empirical database for the ANN model development. They found that there is a non-linear functional relationship between the laser cutting parameters and surface roughness. Additionally, a hybrid approach was also used to optimize surface roughness. Pandey et al. [57] examined a simultaneous optimization of kerf taper angle and surface roughness, which led to the enhancement of 17.32% and 19.16% at the optimal control factor level in surface roughness and kerf taper angle, respectively. In an experimental study on surface roughness in laser cutting of 201 steel plate, the values that were predicted through ANFIS and ANN models were compared with the empirical results. The results highlight the superiority of the ANFIS model over the ANN model with respect to the training speed, convergence precision, and error dimensions [133].

In work performed to analyze the effect of the LBM parameters on surface quality and metallurgical characteristics, the prediction of dross inclusion and surface roughness involvement in the CO_2 laser cutting process was examined by applying the FL model. Based on their findings, it is found that the proposed FL model is a good option to predict the

Table 5
Advantages, limitations, and practical implication of AI techniques.

AI Technique	Advantages	Limitations	Practical implication
ANN	Learning from the former actual data and even insufficient data; Defect tolerance; Reliable and accurate predictions of non-linear and complex behavior; Distributed memory; Capability of parallel processing.	Needing trial and error to select the best network structure (number of hidden layers and neurons); Hardware need for computation; unable to explain the behavior of network;	Improvement in the accuracy for the prediction of parameters in non-linear problems
Fuzzy Logic	Simple formulation; Capability to develop an accurate demonstration of imprecise values of variables.	The performance of the model is highly related to the inference systems, type of membership function, and the number of rules.	It is ideal for imprecise demonstration of the parameters in hard to model problems
Metaheuristic Optimization	Generate several potential answers, Permitting the researcher to choose from several methods to obtain fittest solutions.	Extraction of the suitable new generations after many trial and errors; Dependent on the initial values and parameters.	Selection the fittest answer from several generated solutions for a complex system.
Hybrid Techniques	Eliminating the drawbacks of the single techniques; Capability of Adaptation; Improving the modeling performance with higher speed and smaller error.	It is difficult and time-consuming to formalize and design; limitations on Stopping factors; Dependent on the initial values and parameters.	Permission better modeling performance especially in case of unstable problems.

characteristics of LBM [78]. Addona et al. [135] conducted an investigation on the ANN application to predict the surface roughness and depth in laser milling of poly-methyl-methacrylate (PMMA). In another study, Leon et al. [131] developed an ANN model with a good agreement with experimental data to estimate the surface quality and depth of the workpiece milled by laser. It is concluded that the ANN can be considered as an influential tool to support decision making in LBM to enhance the process advantages as much as possible and improve the surface quality. It was also demonstrated that the well-trained ANN model could be used to predict and analyze the kerf width and surface roughness in the CO_2 laser cutting processes [136]. The architecture of the applied ANN model in the study is shown in Fig. 15.

Selecting the proper process parameters plays a vital role in the successful LBM process with great surface quality and dimensional quality. Ciurana et al. [33] examined the effect of the laser process parameters, including scanning speed, pulse intensity, and pulse frequency on surface roughness and given dimensions using a predictive model developed to this end. In addition, the optimal process parameters of laser micro-milling had been calculated using the PSO technique. Teixidor et al. [137] examined the improvement of surface quality characteristics and dimensional features in laser milling as a fast micro-manufacturing process in the light of process parameters optimization. The effect of laser power, cutting speed, assistant gas pressure, and sheet thickness have been evaluated on the cutting temperature, and surface roughness of laser machined Al60601T6 alloy sheets by Yongbin et al. [134]. They developed an ANN model with a reasonable range of errors to understand the interaction between input-output parameters. It is found that increasing laser power and thickness can be caused by higher surface roughness; While the effect of cutting speed and gas pressure are not considerable.

4.4. Material removal rate

MRR is expressed as the amount of material removed per time unit. Despite the attractive advantages of LBM in comparison to the conventional machining processes, one of the main drawbacks of LBM is the low value of MRR. In this regard, many studies have been done to maximize the MRR in LBM [138–140]. Although, it may not always be ideal to set the parameters for the highest MRR, in particular for high precision cuts [141]. A precise geometry of the manufactured feature can be obtained by an accurate control over the MRR during LBM. In a research conducted by Ahmed et al. [142], reliable mathematical models of MRR and the optimal process parameters were obtained to understand the real behavior of MRR with the lowest surface roughness in LBM of AA 2024. It is found that layer thickness, laser intensity, and pulse frequency have the most notable effect on the percentage of MRR. However, the layer thickness and laser intensity have the largest impact on MRR and surface roughness, respectively. In another study, the material removal rate of laser milled of the difficult-to-cut alloys, including Ti6Al4V, AA 2024, and Inconel 718, has sufficiently predicted with R-square value above 90% by mathematical models [143]. They achieved a desired amount of MRR in the studied alloys by choosing optimal process parameters.

There are several studies on the application of AI in the modeling and optimization of MRR in LBM. Aminian et al. [144] applied three modeling methods, including RSM, ANN, and ANFIS, for the prediction of MRR and taper in LBM and laser welding. The performance of the applied models in the prediction of MRR and tapper of laser machined Al/Al2O3 metal matrix composite are compared in Fig. 16. It became clear that ANFIS provides a more accurate prediction than other methods in both laser processes. Based on this model, the 3D plots of MRR via input parameters are shown in Fig. 17. In a comprehensive study, Chaki et al. [98], four output quality characteristics of Nd:YAG laser cutting process including kerf deviation, kerf width, surface roughness, and MRR have been modeled and optimized by using a hybrid model (entropy-based ANN-PSO integrated model). They investigated the effect of pulse energy, pulse width, and cutting speed as controllable input parameters on quality characteristics. According to the analysis of variance, cutting speed has the most significant influence on the outputs in their study. Considerable improvements have been simultaneously observed in the values of studied quality characteristics using optimal setting parameters.

5. Summary and future direction

Unique privileges of LBM, being a non-contact process, automation adaptability, cost reduction, small HAZ, and resolving the need for finishing operations, have made it a popular choice in the manufacturing industry. The appealing advantage of LBM and its high demand attract a great deal of attention from researchers to enhance this process. It is obvious that understanding the physical phenomenon of the process and evolution of the effect of input parameters on the quality characteristics of LBM is necessary to obtain an efficient process. The number of the influential parameters that must be optimized for achieving the best performance results are one of the main challenges in modeling and optimization of LBM. Implementation of the trial and error method based on experiments does not specify the interaction impacts of the parameters and is time-consuming. Therefore, developing an accurate model and finding the optimal setting parameters of LBM is necessary to reach the best state of the process. Among various proposed approaches, AI has a great influence on the improvement of the current and next generation of LBM. Evidently, AI methods have been successfully used for modeling and optimization LBM. Every aspect of LBM can be considerably enhanced with the fast-developing AI techniques, which can provide more opportunities for the future development of LBM. AI methods provide a general correlation for the knowledge of the phenomena related to laser material processing. Table 5 summarizes the advantages, limitations, and practical implications of the AI techniques reviewed in this paper, which provide guidelines for choosing an appropriate AI technique in future research.

As the LBM performance highly depends on multiple variables, including system parameters, material parameters, and process parameters, AI techniques enable the selection of optimal LBM parameters without the need for a large number of empirical data. In fact, a trained AI model can be used for knowledge acquisition [145]. Additionally, with respect to the complexities of management and control of laser-material interactions, the useful applications of AI techniques can be successfully employed in the design and development of an efficient laser process. In this regard, several potential future directions of AI in LBM are proposed as follows:

- Although ANN and FL are capable of predicting LBM quality characteristics, they still face problems in choosing the appropriate structure. Hybrid methods have been proposed to solve this issue. According to the current research, hybrid methods have a noticeably higher capability compared to single methods in modeling and optimizing the LBM to achieve more accurate and efficient results.
- In ANN modeling, falling into the local minimum is considerably easy. However, prediction accuracy and the fitting effect need improving. The ANFIS model is able to resolve the neural network deficiencies by taking into account the advantages of ANN and FL. ANIFS can be investigated as an efficient alternative for ANN and FL models in future researches.
- A number of advanced AI techniques such as support vector machine (SVM), partial least square (PLS), principal component analysis (PCA) have been developed and applied in modeling and the manufacturing processes during the last decade [51]. Applying these techniques could solve the issue of lack of generalization and over-fitting in ANN [69].
- Among the quality characteristics of the LBM modeled and optimized with AI, most studies have been conducted on kerf, HAZ, and surface roughness. However, less attention has been paid to the other quality characteristics such as MRR, micro-cracks, dross inclusion, thermal

stress, and recast layer that are important characteristics of the process. In future studies, the development of AI modeling and optimizing other neglected characteristics of the laser machined workpiece is essential.

- Proper selection of process parameters in LBM plays a significant role in enhancing the performance of the process. To this end, metaheuristic optimization algorithms can be used in future studies. According to the results of the reviewed studies, utilizing PSO instead of GA in problems with higher dimensions (number of variables), which usually occurs in LBM, will provide a better result. Moreover, other new metaheuristic optimization methods such as ant colony (AC), grey relational analysis (GRA), and simulated annealing (SA) can be used to optimize the process.
- The finite element method (FEM) always faces challenges in the processing time limits and high computational requirements. A combination of FEM and AI methods can significantly reduce the cost and time of the calculations in the LBM modeling and optimization.
- LBM, as a universal tool, needs to be controlled in different states with the fastest time and the lowest energy. AI techniques that are highly adaptable to the automation and online monitoring is a prominent necessity in the next generation of LBM systems.

6. Conclusion

Nowadays, swift development in the utilization of AI in engineering problems is causing a positive change in the efficiency of the systems. Particularly, AI methods have a massive potential to deal with the complex behavior of the manufacturing processes. LBM, due to its dynamic nature, is under the influence of several parameters that make it complicated to model and optimize. Among various methods, AI is superior in terms of accuracy and performance for modeling and optimization of LBM. The applications of the most common AI techniques in modeling and optimizing of the LBM quality characteristics, including geometry characteristics, metallurgy characteristics, surface roughness, and MRR have been reviewed with pros and cons. The results indicate that AI techniques will enable to achieve the optimum LBM performance. It is believed that AI technology has a key role in the modeling, optimization, controlling, and monitoring of LBM. Furthermore, several prospective suggestions have been provided for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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