A review on laser beam machining process modeling and optimization

V B Magdum ¹ and J K Kittur ²

¹ Research scholar, Department of Mechanical Engineering, KLS Gogte Institute of Technology, Belagavi, Karnataka, India, 590008, vbmagdum@rediffmail.com
² Professor, Department of Mechanical Engineering, KLS Gogte Institute of Technology, Belagavi, Karnataka, India, 590008, jkk@git.edu

Abstract. Machining of advanced materials by conventional methods consequences in increased high cutting temperature, high cutting force magnitudes, tool wear, lesser tool life and meagre machined surface. Machining of these materials by conventional methods are originate to be uneconomic. Researches are attracted towards laser beam machining (LBM) between the various nonconventional machining methods. This paper focuses the probable usage of LBM for various materials machining, current progress, benefits and challenges in machining, process parameters and performance characteristics, modeling and optimization. There is need to agreeably designed process parameters which is appropriate to LBM. It is resolute that investigational based modeling and optimization methods are essential to generate model that gives very good fitting with experiments, while determining the effects of several process parameters.

1. Introduction
Advanced engineering materials having the intrinsic physical, mechanical properties. However, machining is related with converting these materials into products. The machinability characteristics pretense various challenges to researcher such as greater cutting force, severe design requirements, complex shape, infrequent size, lesser tool life, upper cutting temperature and meager surface integrity etc. and hence measured as problematic to machining and inefficient. LBM is used for machining nearly entire variety of materials [1-4]. Lasers are extensively used in manufacturing sector. Laser grounded processes are discriminated into various types, including machining, forming, sintering, coating and welding etc. [3]. The figure of LBM is shown in Fig. 1 [5]. In 1960, Theodore H. Maiman built first laser. In LBM, concentrate the laser beam on the workpiece results in melting of material. The melted material is removed by pressurized gas jet. The material removed depends upon the fundamental conditions [4]. Various LBM process parameters affects the performance characteristics are laser power, pulse frequency, pulse width, cutting speed, current, stand off distance, operation mode, wavelength, workpiece material, thickness etc. Thus, selecting the optimal process parameters that would produce the best machining output is the main challenge [2]. The important performance characteristics are surface roughness (Rₐ), kerf taper (Kₜ), kerf width (Kₘ), kerf deviation (K₉), material removal rate (MRR), heat affected zone (HAZ) etc. Kerf taper, kerf width and kerf deviation are three main physiognomies of laser machined kerf and used for decide the kerf geometry [5-8]. The figure of machined kerf is shown in Fig. 2 [9].
2. Material
This segment presents notable studies that have been directed in the field of LBM on material. The important materials which are frequently used for LBM are discussed below:
Ferrous alloys materials are iron based material classified under stainless steel, low carbon ductile steels and hardened steel. These alloys found its application in defense, automotive, chemical, construction, aircraft and medical industry [1,10-12]. Aluminum and its alloys are possessing important properties as high strength to weight ratio, light weight and better electrical, thermal properties. The Nd:YAG laser useful for the machining of these material due to their property of short wavelength, well focusing characteristics and power [10,13]. The outstanding properties like high strength to weight ratio, nontoxicity, strong erosion and corrosion resistance and capability to sustain high strength at high temperature makes titanium and its alloys widely held in automotive, aerospace, nuclear, biomedical and gas turbines industries [1,10,14]. Inconel, waspalloys, hastelloys and udimet are the nickel based alloys. These alloys are another eye catching material over titanium alloys. The abrasives TiC, CrC, MoC make the machining of nickel alloys tough. This effects in shorter tool life, low cutting speed, meager surface quality and results in increase in machining cost [1,15-18]. Mullite, zirconia, alumina and silicon nitride are frequently used ceramic materials in manufacturing industry. Due to their excess brittleness and hardness, low thermal conductivity and diffusivity; machining of ceramics is become difficult. The expeditious improvements in LBM makes it most convenient processing tools [1,10]. Composites are generally formed by mixing or bonding of particles, whiskers in a matrix and fiber. Mixture of fiber or reinforce particle improves the properties like stiffness, thermal properties, abrasive, adhesive, diffusion wear resistance, hardness. High tool wear and successive destruction in the work piece occurred during machining [1,10,19]. Laser beam striking on workpiece results in thermal interface. Very high temperature of laser beam altered physical, chemical and mechanical properties of workpiece. HAZ is form at the surface of cutting edge [10,20-21]. Modeling of HAZ is very complex because of extremely local heat energy to the workpiece and various machining parameter [22-23]. Mathematical, numerical, analytical and soft computing methodologies used for predictions of HAZ [24-27].

3. Modeling and optimization
Manufacturers are interested in LBM due to optimization of the process parameters. Contribution of several process parameters makes LBM highly nonlinear and complex process. Well designed model developed for different performance characteristics [28-31]. The main parameters affecting LBM are beam characteristics, laser characteristics, machining characteristics, quality characteristics, geometry characteristics and metallurgical characteristics [32-35]. Various Modeling and optimization tools are classified as: a. Hard computing methods  b. Soft computing methods

3.1. Hard computing methods
Traditional numerical models are considered as hard computing methods. Various hard computing models used for LBM are given below:
Dr. Genichi Taguchi developed Taguchi method (TM). An orthogonal array (OA) was employed by Taguchi’s design of experiment (DOE). It is the shortest possible experimental matrix of process
parameters combinations. Significance of process parameters on performance characteristics studied through main effect plots by analysis of variance (ANOVA) method [36-41]. The methodology used is select process parameters, recognize the performance characteristics, select an OA, design the experimentation matrix, conduct experiments and record the responses and study the results using S/N ratio and ANOVA [42-45]. Deng in 1982 introduced a Grey relational analysis (GRA) for meagre, inadequate and uncertain system. The experimental data first of all normalized between gray relational grade 0 and 1. Later data preprocessing gray relational coefficient (GRC) are calculated. Grey relation grade (GRG) is the summation of weighted relational coefficients [45-48]. RSM is a collecting of arithmetical and mathematical models applied for reviewing effect of multiple process parameters on performance characteristics and optimization [49-55]. A regression model develops to create relationship among process parameter and performance characteristics. Implication of the developed model studied by predicting a coefficient of determination (R^2). R^2 value ranges between 0 to 1. For higher order interaction 2nd order polynomial is appropriate and it gives better result [26,30,56]. Principal component analysis (PCA) is used orthogonal transformations for bring out patterns in experimental data to mention their similarities and differences. Quality losses are calculated from principal components [57]. Desirability function analysis (DFA) used for converting the multiple response characteristics into single response characteristic named ‘composite desirability’ [58]. The desirability objective function diverges in between ‘0’ and ‘1’ [59].

Hybrid optimization methods used for selecting weighting factor owing to possible relationships among the multi performance characteristics optimum [57]. In TM and PCA, TM used for single objective optimization and S/N ratios got from TM applied in PCA designed for multi objective optimization (MOO). The outcomes of MOO comprise the forecast of optimized process parameter level as well as their proportional inference on multi performance characteristics [57]. TM coupled with DFA is used for optimization of process parameter. The optimum levels of process parameters are recognized on basis of parameters composite desirability value and effect of each process parameter is determined by ANOVA. This hybrid method of TM and DFA is an effective means for optimizing multi response characteristics [60-62]. In RSM based DFA, RSM used for employing to develop experimental models and for optimization of process. When various performance characteristics evaluated, the optimum parameters grasped separately for individual process parameter did not match in entirely cases. In such cases Integrated RSM based DFA used for optimization of process parameter [63-64]. In TM based RSM (TRSM), TM using S/N ratio and orthogonal array applied for finding the effect of process parameters and ANOVA prepared to find the effect of process parameter. The models generated using joint method precisely predicting the responses in machining. Application of TRSM was initiate to be time saving and cost effective [65-66]. A collective method of grey based RSM was discovered for predicting the optimum combination of process parameters. The shortcoming of regression analysis compensates by the grey theory analysis. A quality characteristic of all the responses is calculated as grey relational grade on basis of the grey theory. This was further modelled using RSM for optimization of performance characteristics [67].

3.2. Soft computing methods
A huge volume of experimental data required for modelling and optimization using the traditional statistical tools which is time consuming and nonefficient. These problems are overcome by soft computing methods. These methods provide modeling and optimization with the restricted data [68-71].

Genetic algorithm (GA) improves and optimize performance characteristics of LBM by setting process parameters at optimum level [72-75]. Five phases of GA are initial population, fitness function, selection, crossover and mutation. A fittest individual is select by natural selection [73]. Artificial neural network (ANN) was enthused by the comportment of biological neural networks. Neurons are weighted and interconnected in allotted layers. A multifaceted relationship among process parameters and performance characteristics shown in network can be estimated. The ANN modeling can give good results from incomplete and noisy data, and produce nonlinear and complex relationships [76-78].
A hybrid approach of ANN and GA can accelerate the learning. ANN require huge data and GA requires less data. Hyper parameter are the values required to ANN for perform properly in given problem. In such cases GA use to learn best hyper parameters to ANN. The predicted model is found well in agreement with the experimental data [79-80]. Fuzzy logic (FL) model is developed on the basis of fuzzy set theory. Process parameter denoted as linguistic terms with the grade in between 0 to 1. FL modeling have distinct advantages like mathematical concepts simple, easy to construct and understand, solution to complex problems. FL may not give accurate results but it gives acceptable results [81]. In FL modeling and DFA, Multi response predictive model are established using FL model and MOO of various process parameters are carried out with DFA [81]. Grey Fuzzy method is the combination of GRA and fuzzy logic model. Grey relational coefficients are assigned for individual performance characteristics are deliberate from the experimentally detected data. These GRC are used as input process parameter in the FL modeling to determine the grey relation grades based on fuzzy. Also, GRC are used to determine mutual performance index for various performance characteristics [82].

Many researches attracted due to advantages of LBM over conventional machining for enhancement of viability and machinability benefits difficult to cut material. Modeling and optimization methods are developed to study the significance of process parameters on performance characteristics and their shared interactions effect to forecast the optimal LBM parameter setting.

4. Another section of your paper
The major process parameter and their effect on performance characteristics is discussed below:

4.1. Surface Roughness
It is considered as significant performance characteristic for LBM specimens. It is defined by using of surface finish, crack propagation and striation formation. Surface roughness was measures by using surface measuring devices like surface tester, Talyssurf etc. It is measured in ‘microns’ [53]. Influence of laser power, gas pressure, pulse frequency, pulse width, cutting speed are significant while other parameters like nozzle distance and diameter are less effected. Surface roughness is more influenced by laser power, gas pressure and cutting speed. The percentage influence of cutting speed and gas pressure on surface roughness is 56.62% and 29.38% respectively [36]. Gas pressure and speed have influence of 60.8% and 33.5% respectively on roughness value [38]. Gas pressure is the utmost important factor for surface roughness during LBM [44]. It is found that laser power is more significant as compared to gas pressure and cutting speed on surface roughness [64].

4.2. Kerf width
It specifies the degree of accuracy [72]. It is measured by using microscope [53]. Kerf width is of two types: a) Bottom kerf width b) Top kerf width. It is increases by increasing laser power, gas pressure, pulse frequency and current intensity. It is decreases with decrease in cutting speed. Laser power, gas pressure and cutting speed having percentage influence 88.74%, 7.3% and 3.15% respectively on kerf width [36]. Higher kerf widths are generated due to increase in laser energy. With low pulse energy and pulse frequency the machining process is more reliable and results in small kerf width [72].

4.3. Kerf taper
It is calculated by using eq. (1)

$$Kerf\ taper = \frac{((Top\ kerf\ width-Bottom\ kerf\ width) \times 180)}{(2 \pi \times Workpiece\ thickness)}$$  \hspace{1cm} (1)

The kerf taper decreases by increase in laser power and increases with increase in the piercing time [13]. The result show that small values of pulse width and gas pressure combined with middling to higher values of cutting speed and pulse frequency gives optimum outcomes for kerf taper [73]. It is significantly reducing with increase of pulse width having higher workpiece thickness [76].

4.4. Kerf deviation
It is measured with the help of microscope [53]. It is calculated by using eq. (2)
Kerf deviation = Maximum top kerf width - Minimum top kerf width \hspace{1cm} (2)

As cutting speed rises from 1000 to 3000 mm/min, interaction time among workpiece and laser beam increases results in decreased kerf deviation. But as laser power increases, high energy penetrated into cutting zone and SiC particles presents distributed energy unevenly results in increment of the kerf deviation \cite{53}.

4.5. Heat affected zone
Increase in laser power lead to decrease in HAZ due to fast temperature falling off caused by higher thermal conductivity of aluminum sheets \cite{7}. The width and depth of the HAZ enlarged by increase in the laser power and reduced by increase in the laser scan speed and the laser spot size \cite{24}. Cutting speed and laser power are important for HAZ \cite{26}. Amount of HAZ increases by increase in pulse frequency and pulse width but it decreases with workpiece thickness and power \cite{76}.

4.6. Material removal rate
MRR decides the rate of production and financial side of machining \cite{72}. Pulse frequency has substantial effects on MRR afterward peak power and pulse width. MRR also increases by increase in workpiece thickness \cite{47}. MRR increases by increase in gas pressure and decreases by increase in modulation frequency and wait time \cite{55}. Low pulse energy and pulse frequency produces less thermal energy focused on workpiece is of lesser extent in low MRR. Also, lower values of pulse width and cutting speed utilized laser beam heat entirely to molt the material initiating high MRR. Low range of pulse width and high pulse energy, incident laser beam effects in penetrating melting and vaporizing along the whole workpiece thickness results in rapid increase in MRR. Intensity has noticeable effect on MRR while frequency and pulse overlaps impact are not causative much for the variation in MRR values \cite{75}. Process parameters and performance characteristics used in literature are shown in Fig.3

5. Conclusion
In this study, an effort has been made to review the research carried out in LBM of advanced materials. The outcomes of review are concise as follows:
- LBM can be used to increase the process effectiveness of machining of advanced materials compared to conventional methods.
- Study the effect of process parameters on performance characteristics and optimization of process by modeling and optimization tools.
- Some studies are described multiple process parametric effect on machining of advanced materials. However, no method has been acceptable in a complete way.
- More study is essential to have a good understanding of effect of process parameters and to select the process parameter in the proper way.

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