SYSTEMATIC REVIEW OF OPTIMIZATION TECHNIQUES FOR LASER BEAM MACHINING

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Abstract: *Laser Beam Machining (LBM) has emerged as a versatile non-conventional machining technique widely adopted in aerospace, medical, and automotive industries due to its precision and flexibility. The complexity of LBM processes and the demand for high-quality, resource-efficient manufacturing have driven significant research into optimization methods for process parameters. This systematic review analyzes 228 research publications from 2003 to 2023, categorizing the literature into traditional optimization techniques, multi-criteria decision-making approaches, and advanced computational methods including artificial intelligence and machine learning. The review highlights the evolution and application of methods such as Design of Experiments (DOE), Taguchi, ANOVA, regression models, MOORA, Grey Relational Analysis, and AI-based techniques like artificial neural networks and genetic algorithms. The influence of key process parameters-laser power, cutting speed, gas pressure, standoff distance, and pulse frequency-on critical responses such as surface roughness, material removal rate, kerf width, and heat-affected zone is systematically discussed. The paper provides insights into the effectiveness, advantages, and limitations of various optimization strategies, identifies current challenges, and suggests future research directions for enhancing the performance and sustainability of LBM processes.*

Keywords: **Laser Beam Machining (LBM), Material Removal Rate (MRR), Surface Roughness (SR), Kerf Width, Heat-Affected Zone (HAZ), Dimensional Accuracy, Standoff Distance (SOD), Pulse Frequency, Assist Gas Pressure, Focal Length,Nozzle Diameter**

1. INTRODUCTION

Emerging as one of the most flexible non-conventional machining techniques with several uses in aerospace, medical, and automotive fields is laser beam machining (LBM). In the aerospace, medical, and automotive sectors as well as others LBM finds use (Kharche, 2024). When the laser beam contacts the material surface, the process consists in material removal by melting and vaporization. Using melting and vaporization of metal, Laser Beam Machining (LBM) is a non-conventional technique whereby material removal occurs when the laser beam comes into touch with the metal surface (Shinde, 2016). The increasing complexity of manufacturing needs has made advanced optimization methods necessary to improve laser machining operations' efficiency and quality of output. LBM cannot improve resource-efficiency or system sustainability without optimization methods. The current work attempts to offer a methodical overview of the studies in the field of optimization strategies for LBM (Kharche, 2024). Achieving intended machining results depends critically on the choice of suitable machining settings. Consequently, choosing the suitable machining parameter has become a vital task before beginning the operation (Khan, 2015).
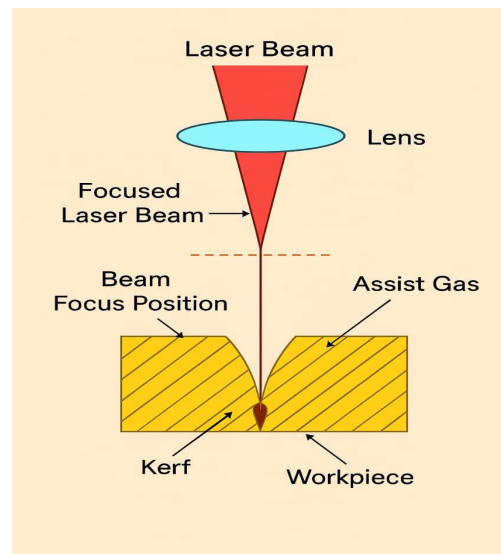
Figure.1 Diagram of Laser Beam Machining

LBM process optimization is a difficult work needing advanced approaches since it contains several goals and restrictions. Many process factors like laser power, cutting speed, assist gas pressure, pulse frequency, and focal length determine the quality of machined products. The machined surface cut by LBM depends on several process factors that influence quality. Most importantly, though, are the laser power, cutting speed, assist gas pressure, nozzle distance, focus length, pulse frequency and pulse width (Shinde, 2016.). The impact of these parameters on surface roughness (SR), material removal rate (MRR), kerf breadth, heat-affected zone (HAZ), and surface hardness have been thoroughly studied by researchers. Surface roughness (SR), material removal rate (MRR), kerf width, heat affected zone (HAZ), and surface hardness (Shinde, 2016) are the key performance metrics in LBM, though.

Over the past two decades, the evolution of optimization methods for LBM has changed dramatically in response to growing research interest in methodical approaches to ascertain the ideal mix of process factors. Reviewed are 228 research publications released overall throughout the past 20 years, from 2003 to 2023. Three main sections—i) optimization techniques, ii) applications of optimization approaches, and iii) difficulties and future directions—Kharche, 2024 classify the literature review Examining their efficacy, limits, and future potential in improving machining performance, this paper offers a thorough evaluation of the several optimization approaches used to LBM.

2. Traditional Optimization Methods for LBM

2.1. Design of Experiments (DOE)

One of the most often used approaches for LBM process parameter optimization is design of experiments (DOE). With a limited number of experimental trials, the method helps scientists to methodically study the impacts of several parameters. Using design of experiments (DOE) analysis improved the laser micro processing method. 17 tests were conducted using a Box-Behnken design (BBD) program to look at how laser settings affect micro processing results (Mahmoud, 2024). Taguchi's orthogonal array design has been very well-known among several DOE methods because its efficiency in parameter screening and optimization.

LBM parameter optimization for several materials and applications has made great use of Taguchi technique. Designing experimental trials using Taguchi's L9 orthogonal array proved challenging (Manjoth, 2016). This method was used, for example, to investigate the effects of standoff distance, cutting speed, and gas pressure on surface roughness, volumetric material removal rate, and dimensional accuracy in the optimization of laser beam machining parameters for Al7075-TiB2 metal matrix composite. We investigated optimization and effect of laser machining process parameters on surface roughness, volumetric material removal rate (VMRR) and dimensional accuracy of composites. While power and nozzle diameter were kept constant with air as assisting gas, standoff distance

(SOD) (0.3 - 0.5mm), cutting speed (1000 - 1200 m/hr) and gas pressure (0.5 - 0.7 bar) were regarded as changeable input factors at three distinct levels. Using Minitab software (version 16), the main effects plot for signal noise ratio (S/N ratio) calculated optimized process parameters for surface roughness, volumetric material removal rate (VMRR) and dimensional accuracy.

Taguchi method application in LBM optimization has also been applied to several materials including titanium alloys, HSLA steel, and Inconel alloys. The machining investigations use Taguchi's L18 orthogonal array. The appropriate mix of the LBM process parameters is assessed using the MOORA approach (Praveen, 2023). Using Taguchi L9 orthogonal array, researchers in a case study on the carbon-dioxide laser beam machining of Inconel 718 alloy found the ideal setting of process parameters including laser power, cutting speed, and gas pressure. The aim of the present work is to find the best values of the process parameters including laser power, cutting speed, gas pressure while milling Inconel-718 material using oxygen gas. The experiment ran on Taguchi L9 orthogonal array. Using laser beam machining and the optimal combination of process parameters, a square washer with four holes of diameter 8 mm and one hole of dimension 64 mm was machined and obtained higher response characteristics computed (Samson, 2020).
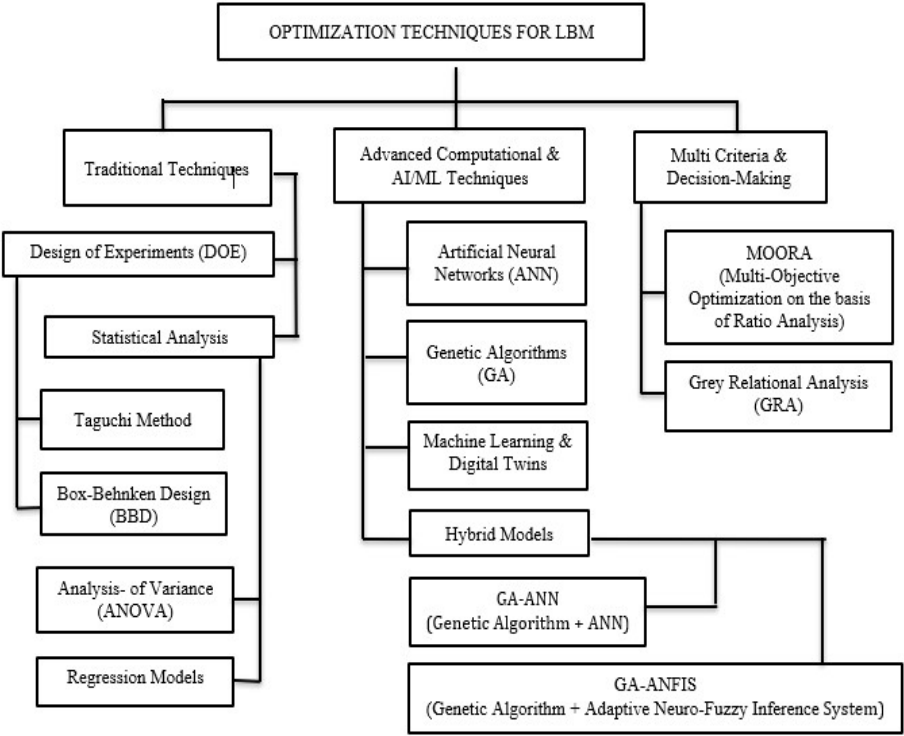

Figure 2. Optimize techniques for LBM

2.2 Analysis of Variance (ANOVA) and Regression Models

Analysis of variance (ANOVA) has frequently been used in conjunction with other optimization techniques to determine the significance of process parameters in LBM. Using Minitab's regression and analysis of variance (ANOVA), the percentage of the effect of parameters by taking cutting speed, laser power, and gas power into account. The results of the major effect and optimization graphs indicate that cutting speed is a significant factor in defining the surface's roughness (Prakash, 2022). The method assists researchers in prioritizing the most crucial components for optimization by statistically validating the impact of each parameter on the response variables. Surface roughness is more influenced by laser power and cutting speed than by gas pressure, according to an ANOVA analysis of the laser beam cutting machining parameters optimization. Cutting speed and laser power are the most significant factors affecting surface roughness, mostly in comparison to gas pressure (Prakash, 2022). Similarly, in the optimization of Al7075-TiB2 metal matrix composite machining, ANOVA results showed that the most significant factor for surface roughness was cutting speed (56.38%), which was followed by standoff distance (41.03%) and gas pressure (2.6%). The significant effects of gas pressure, cutting speed, and standoff

distance (SOD) on surface roughness, volumetric material removal rate (VMRR), and dimensional error were calculated using the analysis of variance (ANOVA) technique. According to the results, the most crucial factor for surface roughness is cutting speed (56.38%), which is followed by standoff distance (41.03%) and gas pressure (2.6%). In terms of volumetric material removal rate, gas pressure (42.32%) was shown to be the most significant factor, followed by cutting speed (33.60%) and standoff distance (24.06%). For volumetric material removal (VMRR), gas pressure (42.32%) is the most crucial factor, followed by cutting speed (33.60%) and standoff distance (24.06%). Menjoth (2016).

In LBM, regression models have also been used extensively to construct mathematical correlations between process parameters and performance metrics. Using analysis of variance, the combined influence of machining performance measurements is investigated to find the significance of the outcome (Praveen, 2023). These models help to identify ideal settings without much trial by allowing prediction of machining results for specific parameter combinations. In the case of HSLA steel machining, surface roughness and kerf width were among the response variables and LBM process parameters for which regression models were created. The present work is aimed on examining surface roughness and kerf width of HSLA steel under the influence of laser beam machining process parameters. As such, the effect of the factors on machining reactions was investigated. Examined is the surface geometry of the machined surface of the ideal set of parameters (Praveen, 2023).

2.3 MOORA Method and Multi-Criteria Decision Making

One effective strategy for resolving multi-objective optimization issues in LBM is the Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method. In order to tackle various multi-objective problems that arise in the real-time manufacturing industries, the current study investigates a unique technique called multi-objective optimization on the basis of ratio analysis (MOORA). This work focuses on using the MOORA approach to solve issues with various criteria in non-traditional machining processes (Khan, 2015).

Wire-Electric Discharge Machining (WEDM), Plasma Arc Cutting (PAC), Electro Chemical Micro Machining (ECMM), Electro Chemical Machining (ECM), Abrasive Jet Machining (AJM), Abrasive Water Jet Machining (AWJM), Ultrasonic Machining (USM), and Laser Beam Machining (LBM) are just a few of the unconventional machining processes that have successfully used the technique. The main focus of this study is on the following processes: Abrasive Jet Machining (AJM), Abrasive Water Jet Machining (AWJM), Ultrasonic Machining (USM), Laser Beam Machining (LBM), Plasma Arc Cutting (PAC), Electro Chemical Micro Machining (ECMM), Electro Chemical Machining (ECM), Wire-Electric Discharge Machining (WEDM), and Laser Cutting Process. The choice of appropriate machining parameters is one of nine NTM multi-criteria problems that have been examined. The MOORA method's ideal input variable settings are almost identical to those determined by previous researchers (Khan, 2015).

The MOORA method was used to evaluate the best combination of process parameters, while taking into consideration the number of response variables in recent research on the optimization of LBM process parameters for HSLA steel. The proper combination of the LBM process parameters is evaluated by the MOORA method. To find the significance of the result, the sum effect of machining performance measures is analyzed through analysis of variance (Praveen, 2023). The approach allowed multiple objectives, like kerf width and surface roughness reduction, to be integrated into a single optimization problem.

Other multi-criteria decision-making methods like Grey Relational Analysis (GRA) have also been widely used for the optimization of LBM parameters. Effect and Optimization of Laser Beam Machining Parameters using Taguchi and GRA Method: A Review (Bo, 2014) The Grey Relational Analysis method was successfully employed in the laser drilling process optimization of AISI 303 material, allowing simultaneous optimization of more than one response variable like surface roughness and heat-affected zone. The objective of the current study is to maximize surface roughness (Ra) and HAZ in fibre laser drilling of AISI 303 material through Taguchi-based grey relational analysis (GRA). Based on the GRA technique, the suggested optimum process parameter combination is flushing pressure of 30 Pa, laser power of 2000 W and pulse frequency of 1500 Hz for concurrent

optimization of Ra and HAZ. Through analysis of variance, the frequency of pulse is found to be the most affected process parameters on laser drilling process performance (Reddy, 2021).

Table 1. Effect of LBM Process Parameters on Responses

Process Parameter	Response(s)	Effects and Influences
Laser Power	Surface Roughness (SR), MRR, HAZ, Kerf Width	- Higher power increases MRR and kerf width.
Cutting Speed	Surface Roughness, MRR, Dimensional Accuracy	- Higher speed reduces HAZ and kerf width.
Assist Gas Pressure	MRR, Surface Roughness, Kerf Width, HAZ	- Higher pressure improves material removal and reduces dross. - Excessive pressure may widen kerf and HAZ.
Standoff Distance (SOD)	Surface Roughness, MRR, Dimensional Error	- Optimal SOD improves cut quality. - Too large or small SOD increases surface roughness and dimensional error.
Pulse Frequency	Surface Roughness, HAZ, MRR	- Higher frequency can decrease HAZ and improve finish. - Very high frequency may reduce MRR.
Pulse Width/Duration	Surface Roughness, HAZ	- Shorter pulses reduce HAZ and improve precision. - Longer pulses increase heat input and roughness.
Focal Length	Kerf Width, Surface Roughness	- Proper focus minimizes kerf width and improves finish. - Misfocus increases kerf width and roughness.
Nozzle Diameter	Kerf Width, Surface Finish	- Larger diameter may increase kerf width. - Smaller diameter can improve precision but may reduce MRR.
Material Properties	All responses	- Material type, reflectivity, and thermal properties affect absorption, MRR, and quality of cut.

3. Advanced Computational and AI/ML Optimization Techniques

3.1 Artificial Intelligence and Machine Learning Approaches

The use of artificial intelligence (AI) and machine learning (ML) approaches has transformed the process of laser beam machining optimization over the last few years. This article discusses the infusion of artificial intelligence (AI) and high-end digital technologies into laser processing and their applications for improving precision, efficiency, and process control. The research investigates the use of digital twins and machine learning (ML) in the optimization of laser machining, minimizing defects, and enhancing laser–material interaction analysis. Focus is given to AI's potential for additive manufacturing and microprocessing, especially real-time monitoring, defect prediction, and parameter optimization (Murzin, 2024). These sophisticated computational techniques have several benefits compared to standard optimization methods, especially when dealing with complex, non-linear relationships between machining results and process parameters.

Artificial Neural Networks (ANNs) have been applied effectively for modeling and optimization of different aspects of LBM processes. In laser processing, though, there is a nonlinear relationship between process parameters and the quality of processing, which is quite complicated, such that it is difficult to build high-accuracy predictive models, while the inner link between these two aspects is still not fully exposed. Against this background,

this research proposes the application of machine learning methods to investigate the intrinsic correlation between processing quality and process parameters and constructs a 5-13-5 type BP neural network predictive model (Zhang, 2024). In another research dealing with carbon fiber reinforced polymer laser machining, researchers created a high-precision predictive model based on neural networks to determine laser processing parameters and machining quality relationships. To solve the problem of thermal damage caused by laser processing of carbon fiber reinforced polymer (CFRP), researchers have carried out an optimization study of process parameters in laser processing of CFRP. Their objective is to clarify the correlation between process parameters and processing quality to reduce thermal damage (Zhang, 2024). The back-propagation neural network model showed good prediction accuracy, with average errors of 5% for surface heat-affected zone, 2.9% for groove width, 5.9% for cross-sectional heat-affected zone, 1.8% for groove depth, and 4.5% for aspect ratio. The findings reveal that the BP neural network prediction model produces average errors of 5% in surface heat-affected zone (HAZ), 2.9% in groove width, 5.9% in cross-sectional HAZ, 1.8% in groove depth, and 4.5% in aspect ratio, showing a fairly high degree of accuracy but with significant fluctuations (Zhang, 2024).

The integration of genetic algorithms with neural networks has further improved the optimization potential for LBM processes. Genetic algorithms are then utilized to optimize the weights and thresholds of the BP neural network, and the model is then validated. The GA-BP model, in the prediction of surface HAZ and groove width, has errors of 4.5% and 2.7%, respectively, which are lower compared to the BP model, showing greater predictive accuracy (Zhang, 2024). In optimizing kerf width in laser beam machining of titanium alloy, scientists combined genetic algorithm with adaptive neuro-fuzzy inference system (GA-ANFIS) for creating a high-precision prediction model. In this study, adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm tuned ANFIS (GA-ANFIS) were employed to forecast the KW on a titanium alloy workpiece during DLBM. Whereas, in certain situations, soft computing techniques of the traditional type cannot procure high accuracy, in this research study, an attempt was made to present the GA-based ANFIS approach for kerf width prediction during groove machining of a titanium alloy workpiece employing the DLBM process from experimental data of all possible 50 combinations of the process parameters (Ji, 2024). The GA-ANFIS model showed better prediction performance with lesser error parameters and greater accuracy than the conventional models. The prediction performance of the GA-ANFIS model was improved with less value for error parameters (MSE, RMSE, MAE) and greater R2 value of 0.98 for various folds. Comparison with other state-of-the-art models also revealed the superiority of the GA-ANFIS predictive model, as its performance was better across all measures (Ji, 2024).

3.2 Nature-Inspired Optimization Algorithms

Nature-inspired optimization algorithms have come forward as useful tools for the parameter optimization of LBM. Among them, the Artificial Bee Colony (ABC) algorithm has shown to be highly effective for finding optimal process parameters in Nd:YAG laser beam machining. Nd:YAG laser beam machining (LBM) process holds enormous potential for manufacturing complex shaped microproducts with its distinct properties. In actual applications, for example, drilling, grooving, cutting, or scribing, the best set of Nd:YAG LBM process parameters must be found to offer the required machining performance. In this paper, the use of artificial bee colony (ABC) algorithm is utilized to find the best set of Nd:YAG LBM process parameters while taking into consideration both single and multiobjective optimization of the responses (Mukherjee, 2013).

ABC algorithm has demonstrated better performance than other population-based algorithms like genetic algorithm, particle swarm optimization, and ant colony optimization. Comparative analysis with other population-based algorithms like genetic algorithm, particle swarm optimization, and ant colony optimization algorithm validates the global usability and acceptability of ABC algorithm for parametric optimization. In this algorithm, information exchange between the onlooker bees reduces the search iteration for global optimum and prevents suboptimal solution generation. Its superiority over the other optimization algorithms is also illustrated by the outcomes of two sample paired -tests (Mukherjee, 2013). The ability of the algorithm to reduce search iterations for global optimum solutions and prevent suboptimal results renders it especially useful for intricate LBM parameter optimization problems.

Genetic Algorithms (GA) have also been used very widely for multi-objective optimization of LBM process parameters. Lastly, the best process parameters for minimum KW and SR, obtained from gray relational–based (GRB) multi-response optimization (MRO) technique, were 20 W (level 2) laser power, 22 mm (level 5) standoff distance, 300 mm/min (level 5) feed rate, 85% (level 5) duty cycle, and 18 kHz (level 3) frequency (Ji, 2024). The evolutionary strategy of GA allows the search of enormous parameter spaces and the determination of near-optimal solutions for many conflicting objectives, e.g., maximizing material removal rate while minimizing surface roughness and heat-affected zone.

3.3 Digital Twins and Simulation-Based Optimization

The digital twin concept has appeared as a revolutionary method for optimizing laser processing methods. This paper discusses the revolutionary influence of digital engineering on photonic technologies, with a focus on developments in laser processing using digital models, artificial intelligence (AI), and freeform optics. It offers an extensive overview of how these technologies improve efficiency, accuracy, and control in manufacturing processes. Digital models play a central role in predicting and optimizing thermal effects in laser processing, thus minimizing material deformation and defects (Murzin, 2024). Digital twins allow for the development of virtual copies of physical laser machining systems, allowing for real-time monitoring, simulation, and optimization of process parameters without extensive physical testing.

Table 2. Categorization of Literature Based on Optimization Techniques in LBM

Advanced Computational/AI	Optimization Technique	Applications/Focus
Traditional Methods	Design of Experiments (DOE) Taguchi Method Analysis of Variance (ANOVA) Regression Models	Parameter screening, process optimization for materials like Al7075-TiB2, Inconel 718, titanium alloys Optimization of SR, MRR, kerf width, dimensional accuracy Significance analysis of process parameters; response prioritization Predictive modeling of SR, kerf width, MRR, etc.
Multi-Criteria Decision Making	MOORA (Multi-Objective Optimization on Ratio Analysis) Grey Relational Analysis (GRA) Artificial Neural Networks (ANN)	Multi-objective optimization (e.g., minimizing SR & kerf width simultaneously) Simultaneous optimization of SR, HAZ, etc. (e.g., laser drilling of AISI 303) Predictive modeling and optimization of process parameters for CFRP, titanium alloys, etc.
Advanced Computational/AI	Genetic Algorithms (GA) Hybrid AI Techniques (GA-ANN, Digital Twins) Machine Learning (ML)	Combined with ANN for parameter optimization, especially for minimizing HAZ, kerf width, etc. Real-time monitoring, defect prediction, and parameter optimization in advanced LBM applications Data-driven optimization, digital twins for process control

The combination of digital twins with artificial intelligence has greatly improved the optimization potential for laser-based manufacturing processes. The combination of AI further enhances these models, enhancing productivity and quality in applications like micromachining and cladding. Moreover, the integration of AI with freeform optics propels laser technology forward by allowing for real-time adaptation and beam profiles that can

be tailored, enhancing processing flexibility and minimizing material damage. Digital twin utilization is also discussed as one of the principal developments in laser-based manufacturing, providing dramatic enhancements in process optimization, defect reduction, and system efficiency (Murzin, 2024). By integrating real-time monitoring, machine learning, and physics-based modelling, digital twins enable accurate simulations and predictions, resulting in more efficient and trustworthy manufacturing practices. By integrating real-time monitoring, machine learning, and physics-based modelling, digital twins enable accurate simulations and predictions, resulting in more efficient and trustworthy manufacturing practices. In general, the combination of digital twins, AI, and freeform optics in laser processing represents a remarkable advancement in manufacturing technology. These developments altogether increase accuracy, efficiency, and flexibility, leading to better product quality and lower operational expenses (Murzin, 2024).

Simulation optimization methods have also been extensively used for LBM process parameter optimization. Researchers have used COMSOL software for theoretical calculations to find the distribution of surface and subsurface temperatures in a study on the optimization of laser micro/nano processing of silicon and quartz to identify the best laser parameters. The COMSOL software was used to make theoretical calculations in order to calculate the silicon and quartz surface temperatures and subsurface temperature distribution. Maximum temperatures recorded were around 5700 K for silicon and 2630 K for quartz. Numerical optimization based on DOE software enhanced the synthesis of silicon nanoparticles and quartz microlens, resulting in silicon nanoparticles wavelength peak and absorption peak values of 318.2 nm and 0.39, respectively (Mahmoud, 2024). The combination of simulation with experimental design of experiments (DOE) analysis has been found to be especially useful in improving laser micro processing methods.

4. Material-Specific Optimization Approaches

4.1 Optimization for Metallic Materials

Optimization of LBM parameters for metal materials, especially superalloys such as Inconel and titanium alloys, has been of interest to researchers due to their broad applications in the aerospace and biomedical sectors. For Inconel 718 alloy, which demonstrates excellent physical and mechanical properties under high temperatures, researchers have attempted to optimize LBM parameters for desired surface finish and material removal rates. Carbon-dioxide laser beam machining (LBM) machining is applied for machining hard and complex shapes which are unimaginable with traditional machining techniques. Inconel 718 has its major applications in the manufacturing of high-pressure turbine parts and aerospace industry structural components. Inconel 718 alloy contains high physical and mechanical properties at higher temperature, Strength-to-density ratio and improved corrosion resistance (Samson, 2020).

By optimization research with Taguchi approach, researchers established the best set of process parameters such as cutting speed, laser power, gas pressure, focal point, and pulse frequency for reducing surface roughness and increasing material removal rate. The optimal value of surface roughness was discovered to be 3.5µm and likewise material removal rate to be 45.56 m3/min while operated at cutting speed of 2.1m/min, type of cut as rough, 1mm focal point and gas pressure of 4000bar, The influence of input variables on different response parameters namely surface roughness (Ra), Heat affected zone thickness (HAZ), material removal rate (MRR), Taper, Circularity, hardness were investigated (Samson, 2020).

Likewise, in the case of titanium alloys, which have extensive applications in biomedical and aeronautical engineering, researchers used sophisticated optimization strategies like genetic algorithm tuned adaptive neuro-fuzzy inference system to enhance process parameters. In power diode laser beam machining (DLBM) machining, kerf width (KW) and surface roughness (SR) play crucial roles while assessing the quality of cutting for the machined specimens. Besides establishing the impact of process parameters on these variables, it is highly crucial to employ multi-response optimization strategies to them for better processing of specimens, particularly for hard-to-machine materials. In the present study, adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm-tuned ANFIS

(GA-ANFIS) were utilized to model the KW on a titanium alloy workpiece during DLBM. Five machining process parameters, i.e., power diode, standoff distance, feed rate, duty cycle, and frequency, were employed for model development because they are related to KW (Ji, 2024). The best process parameters for minimum kerf width and surface roughness were established using multi-response optimization techniques like grey relational analysis.

Table 3. Materials Used in Laser Machining Applications

Material	Industry	References
Al7075-TiBâ,, Metal Matrix Composite	Aerospace, Automotive	Manjoth, 2016
Titanium Alloys	Medical, Aerospace	Samson, 2020; General Review
HSLA Steel (High Strength Low Alloy)	Automotive, Structural	Praveen, 2023
Inconel 718 Alloy	Aerospace, Power Generation	Samson, 2020
AISI 303 Stainless Steel	General Engineering	Bo, 2014; Reddy, 2021
Carbon Fiber Reinforced Polymer (CFRP)	Aerospace, High-Performance	Zhang, 2024
General Metals (e.g., Steel, Aluminum, Alloys)	Multiple Industries	Shinde, 2016; Kharche, 2024

4.2 Optimization for Ceramics and Composites

The process optimization of LBM parameters in the case of ceramic and composite materials is special, as both involve heterogeneous material composition and distinct properties. In alumina ceramics, which are especially known for the high level of corrosion and thermal resistance but present difficulties during machining because they are brittle, investigators have tested diverse optimization strategies with the goal to improve machining quality. Alumina, famous for its excellent resistance to heat and corrosion, offers a tough challenge in machining due to its brittleness. However, laser machining has proven to be a very appropriate process for handling hard and brittle materials such as alumina. Although conventional machining methods can work as well, they tend to require long machining times and exceedingly high tool wear rates, which increase the entire machining cost (Himawan, 2023).

Machine learning methods have shown special efficacy in the process optimization of laser machining of alumina ceramics. Laser machining is a very versatile non-contact manufacturing method that has been used extensively in academia and industry. On account of nonlinear light-matter interactions, simulation methods are of utmost importance, as they contribute to maximizing the machining quality by providing understanding of the inter-relations among the laser processing parameters. Conversely, experimental optimization of processing parameters suggests a systematic, and therefore time-consuming, exploration of the accessible processing parameter space. A smart approach is to utilize machine learning (ML) methods to learn the correlation between picosecond laser machining parameters for identifying suitable parameter combinations to produce the desired cuts on industrial-grade alumina ceramic with deep, smooth and defect-free patterns (Behbahani, 2022). Neural networks have been especially effective in the prediction of the connections between laser parameters and machining results for ceramics, allowing channel size and surface finish to be optimized. Laser parameters like beam amplitude and frequency, scanner passing speed and number of passes over the surface, and the vertical distance of the scanner from the sample surface are employed in predicting the depth, top width, and bottom width of engraved channels utilizing ML models. Due to the intricate relationship among laser parameters, it is established that Neural Networks (NN) are the most effective in output prediction. Having an ML model that identifies the relationship between the interconnection of laser parameters and the dimensions of the engraved channel, one is able to forecast the input parameters needed to realize a desired channel geometry. This approach drastically lowers the expense and effort of experimental laser machining during the development stage without sacrificing accuracy or performance (Behbahani, 2022).

For carbon fiber reinforced polymer (CFRP) composites, which are prone to thermal damage during laser processing, researchers have emphasized the optimization of process parameters to reduce thermal effects while ensuring machining efficiency. To solve the problem of thermal damage caused by laser processing of carbon fiber reinforced polymer (CFRP), scientists have carried out an optimization study of process parameters in laser processing of CFRP. They are trying to explain the correlation between process parameters and processing quality to reduce thermal damage. But in laser processing, there is a complicated nonlinear relationship between processing quality and process parameters, and it is difficult to build high-precision predictive models, although the intrinsic relationship between these two factors is still not fully unveiled (Zhang, 2024). Genetic algorithm optimized neural networks have been shown to possess great potential in building high-precision predictive models for optimizing CFRP laser machining.

5. Challenges and Future Directions

5.1 Current Limitations in LBM Optimization

In spite of tremendous progress in optimization methods of laser beam machining, some challenges and limitations still remain. The article also considers arising challenges like adapting AI models to complex material behaviors and integrating intelligent systems into current manufacturing systems (Murzin, 2024). The adaptation of AI models to complex material behaviors, especially in heterogeneous and composite materials, is one of the main challenges. The non-linear couplings between laser beam and other materials, combined with the intricacy of material removal and heat transfer mechanisms, pose challenges in establishing universally valid optimization models.

The incorporation of high-level optimization systems into current manufacturing environments is another major challenge. Although issues like the requirement for specialized knowledge and investment in new technologies remain, this article highlights the substantial benefits of combining computer science with laser processing (Murzin, 2024). The application of advanced AI-based optimization methods typically involves specialized knowledge and high investment in new technologies, which can restrict their implementation in small and medium-sized manufacturing companies.

5.2 Emerging Trends and Future Research Directions

There are some emerging trends and future areas of research identified in the LBM optimization domain. The innovation of the current systematic review article is to provide a future area of research direction in the optimization techniques of LBM domain. Due to the proposed research, an effective and sustainable LBM with the specified performance will be created in the minimum possible timeframe (Kharche, 2024). The merging of real-time monitoring with adaptive control systems is a promising path for the development of robustness and responsiveness in LBM optimization. This paper explores the computer science contribution to the improvement of laser processing methods, highlighting the revolutionary nature of their merging with manufacturing. It addresses important aspects where computational approaches improve the accuracy, flexibility, and efficiency of laser operations. With the aid of sophisticated modeling and simulation methods, material behavior during laser irradiation was better understood, and process parameters could be optimized, along with the reduction of defects. The function of intelligent control systems based on machine learning and artificial intelligence was also investigated, illustrating how real-time data processing and adjustments result in enhanced process quality and reliability (Murzin, 2024).

Hybrid optimization strategies, blending conventional statistical techniques with sophisticated machine learning methods, hold great promise for resolving the multifaceted nature of multi-objective optimization issues in LBM. Additionally, machine learning in the speeding up of the LAM process optimization and design of new materials is also envisioned (Su, 2024). Such hybrid methods are able to tap into the explanatory capabilities of statistical techniques and tap into the learning abilities of machine learning algorithms.

The implementation of transfer learning and federated learning methodologies has the potential for creating more generalizable optimization models that can be transferred to

various materials and machining environments with little retraining. This paper aims to give a summary of ML's role in advancing femtosecond laser machining to a more determinist and efficient method. Taking advantage of data from laser parameters and in-situ and ex-situ imaging of processing results, ML methods—ranging from supervised learning, unsupervised learning, to reinforcement learning—can make a significant impact on process monitoring, process modeling and prediction, parameter optimisation, and self-driving beam path planning. Such advances drive femtosecond laser towards a critical tool for micro-and nanomanufacturing, allowing precise control over machining results and enriching our understanding of the laser machining process (Gao, 2024). Such advanced machine learning strategies may be able to effectively minimize the experimental work in optimizing LBM parameters for new materials or applications.

Moreover, advancements in more advanced digital twins and physics-informed neural networks present promising directions toward improving the precision and effectiveness of simulation-based optimization methods in LBM. Outstanding accomplishments are enumerated in numerical modeling, machine learning applications, and geometry optimization of optical systems as well as integrating dynamic DOEs with laser systems for adaptive beam control. The paper encompasses the creation of sophisticated diffractive structures with enhanced properties and novel optimization strategies (Murzin, 2025). These sophisticated computational models can couple physical understanding of laser-material interactions with data-driven learning methods to provide more precise predictions of machining results and more efficient optimization of process parameters.

6. Conclusion

This systematic review has elaborately discussed the different optimization methods used in laser beam machining, from the conventional ones like design of experiments, Taguchi method, and ANOVA to cutting-edge computational methodologies like artificial intelligence, machine learning, and digital twins. The review has emphasized the development of these methods and their usage over different materials and machining conditions.

Conventional optimization techniques, specifically Taguchi's orthogonal array planning and ANOVA, remain basic methods for parameter screening and significance testing in LBM optimization. They are capable of offering useful information on the relative importance of various process parameters and their interactions, allowing optimal parameter combinations to be identified with less experimental effort.

Advanced computational methods, especially AI and ML methodologies, have exhibited great promise in tackling the complexity of LBM optimization issues. Neural networks, genetic algorithms, and hybrid models have proven to excel in the task of simulating intricate non-linear interactions between process factors and machining responses, facilitating better prediction and optimization of LBM processes.

The combination of simulation-based optimization methodologies with digital twins is a key breakthrough in LBM optimization, as it allows virtual experimentation and real-time process parameter optimization. These methodologies use physics-based models and real-time monitoring to increase the accuracy, efficiency, and flexibility of laser machining processes.

Material-specific optimization methods have been established to tackle the specific challenges related to various materials, such as metals, superalloys, ceramics, and composites. These methods consider the unique material properties and machining needs, allowing for the creation of application-specific optimization strategies.

Notwithstanding major strides, there are still challenges with the transfer of AI models to intricate material behaviors and the integration of high-level optimization systems within current manufacturing systems. Some future research directions include the creation of hybrid optimization strategies, transfer learning methods, and more advanced digital twins to increase the robustness, generalizability, and efficiency of LBM optimization.

In summary, the ongoing development of optimization methods in laser beam machining has tremendous potential to accelerate precision, efficiency, and sustainability in manufacturing operations. By combining the complementary strengths of conventional and innovative optimization methods, researchers and practitioners are capable of formulating

better approaches to optimizing LBM processes in a wide range of materials and applications.

Appendix

A. List of Key Terms and Abbreviations

Abbreviation	Description
LBM	Laser Beam Machining
MRR	Material Removal Rate
SR	Surface Roughness
HAZ	Heat-Affected Zone
KW	Kerf Width
SOD	Standoff Distance
DOE	Design of Experiments
ANOVA	Analysis of Variance
GRA	Grey Relational Analysis
MOORA	Multi-Objective Optimization on the Basis of Ratio Analysis
ANN	Artificial Neural Network
GA	Genetic Algorithm
ANFIS	Adaptive Neuro-Fuzzy Inference System
ABC	Artificial Bee Colony Algorithm
ML	Machine Learning
AI	Artificial Intelligence
Digital Twin	A virtual model that mirrors real-world LBM systems for simulation and optimization

B. Optimization Techniques Categorization

Category	Techniques/Models Used
Traditional Methods	Taguchi Method, DOE, ANOVA, Regression Models
Multi-Criteria Decision Making	MOORA, GRA
Artificial Intelligence & Machine Learning	ANN, GA, ANFIS, GA-ANFIS, ML Models
Nature-Inspired Algorithms	Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO)
Simulation-Based Optimization	Digital Twins, COMSOL Simulation

C. Key Process Parameters and Effects

Process Parameter	Influences
Laser Power	↑ MRR, ↑ KW, ↑ HAZ, ↑ SR
Cutting Speed	↑ Dimensional Accuracy, ↓ HAZ, ↓ KW; but ↑ SR if too high
Assist Gas Pressure	↑ MRR, ↓ Dross, ↑ KW & HAZ (if excessive)
Pulse Frequency	↓ HAZ, ↑ Finish, ↓ MRR (if too high)
Standoff Distance	Affects SR, MRR, and Dimensional Error

Process Parameter	Influences
Pulse Width	↓ HAZ (shorter), ↑ Roughness (longer)
Focal Length	Affects KW and Surface Finish
Nozzle Diameter	Affects Precision and MRR

D. Material Categories Studied

Material Type	Examples / Application Industries
Metals & Alloys	Al7075-TiB$_2$, Inconel 718, HSLA Steel, Titanium Alloys
Polymers & Composites	Carbon Fiber Reinforced Polymer (CFRP)
Ceramics	Alumina Ceramic

E. Optimization Objectives by Material

Material	Key Optimization Objectives
Inconel 718	Minimize SR, Maximize MRR, Reduce HAZ
Titanium Alloys	Minimize KW, SR using GA-ANFIS
CFRP	Reduce thermal damage using ANN and ML
Alumina Ceramics	Achieve smooth channels and precision with minimal cracking

REFERENCES

11.1. Journal Article

[1] *Kharche, P., & Patil, V. H. (2024). Systematic review of optimization techniques for laser beam machining. Engineering Research Express. https://doi.org/10.1088/2631-8695/ad594b*

[2] *Shinde, A. D., & Kubade, P. R. (2016). Current research and development in laser beam machining (LBM): a review. International Journal of Scientific Engineering and Research. https://doi.org/10.70729/ijser151032*

[3] *Khan, A., & Maity, K. (2015). Parametric optimization of some non-conventional machining processes using MOORA method. International Journal of Engineering Research in Africa. https://doi.org/10.4028/www.scientific.net/jera.20.19*

[4] *Mahmoud, M. J., Rasheed, B. G., & Hanon, M. M. (2024). Optimization of laser micro/nano processing of silicon and quartz. International Journal of Nanoelectronics and Materials. https://doi.org/10.58915/ijneam.v17ijune.840*

[5] *Prakash, R., Sridevi, K., & Bellad, S. (2022). Optimization of laser beam cutting machining parameters using ANOVA and regression models. ECS Transactions. https://doi.org/10.1149/10701.14975ecst*

[6] *Murzin, S. (2024). Artificial intelligence-driven innovations in laser processing of metallic materials. Metals. https://doi.org/10.3390/met14121458*

[7] *Zhang, G. et al. (2024). High-accuracy predictive model for carbon fiber reinforced polymer laser machining quality using neural networks. Journal of Laser Applications. https://doi.org/10.2351/7.0001313*

[8] *Ji, M. et al. (2024). Prediction and optimization of kerf width in laser beam machining of titanium alloy using genetic algorithm tuned adaptive neuro-fuzzy inference system. The International Journal of Advanced Manufacturing Technology. https://doi.org/10.1007/s00170-024-13681-x*

[9] *Mukherjee, R., Goswami, D., & Chakraborty, S. (2013). Parametric optimization of Nd:YAG laser beam machining process using artificial bee colony algorithm. Journal of Industrial Engineering. https://doi.org/10.1155/2013/570250*

[10] *Tarawan, H. et al. (2023). A review on laser machining of alumina ceramic. Suranaree*

Journal of Science and Technology. https://doi.org/10.55766/sujst-2023-03-e0887

[11] *Behbahani, R. et al. (2022). Machine learning-driven process of alumina ceramics laser machining. Physica Scripta. https://doi.org/10.1088/1402-4896/aca3da*

[12] *Su, J. et al. (2024). Recent innovations in laser additive manufacturing of titanium alloys. International Journal of Extreme Manufacturing. https://doi.org/10.1088/2631-7990/ad2545*

[13] *Gao, J. et al. (2024). Machine-learning-enhanced femtosecond-laser machining: Towards an efficient and deterministic process control. MATEC Web of Conferences. https://doi.org/10.1051/matecconf/202440104004*

[14] *Murzin, S. (2025).* Digital engineering in diffractive optics for precision laser processing. *Photonics. https://doi.org/10.3390/photonics12040306*

[15] *Murzin, S. (2024). Computer science integrations with laser processing for advanced solutions. Photonics. https://doi.org/10.3390/photonics11111082*

11.2. Book

[16] *H. S Steen, W. M., & Mazumder, J. (2010). Laser Material Processing (4th ed.). Springer. https://doi.org/10.1007/978-1-84996-062-5*

11.3. Chapter in a Book

[17] *Yilbas, B. S., & Sahin, A. Z. (2011). Laser cutting: Process and modeling. In B. S. Yilbas & S. Keles (Eds.), Laser Machining: Fundamentals and Applications (pp. 89–117). Springer. https://doi.org/10.1007/978-3-642-20834-2_5*

11.4. Conference Proceedings

[18] *Manjoth, S., Keshavamurthy, R., & Kumar, G. S. P. (2016). Optimization and analysis of laser beam machining parameters for Al7075-TiB$_2$ in-situ composite. IOP Conference Series: Materials Science and Engineering. https://doi.org/10.1088/1757-899x/149/1/012013.*

[19] *Praveen, D. et al. (2023). Optimization of laser beam machining process parameters of HSLA steel using MOORA. Advances in Materials Research. https://doi.org/10.4028/p-426xau*

[20] *Samson, R. M. et al. (2020). Performance analysis of process variables on laser beam machining of Inconel-718 alloy. IOP Conference Series: Materials Science and Engineering. https://doi.org/10.1088/1757-899x/912/3/032036*

[21] *Bo, Z. (2014). Precision machining technology of optical glass. Advanced Materials Research. https://doi.org/10.4028/b-vrz58z*

[22] *Reddy, V. C. et al. (2021). Analysis and optimization of laser drilling process during machining of AISI 303 material using grey relational analysis approach. SN Applied Sciences. https://doi.org/10.1007/s42452-021-04337-6*

11.5. Patent

[23] *Naik, N. V., & Sharma, R. (2018). Method and apparatus for adaptive laser machining with real-time parameter optimization. U.S. Patent No. 10,028,357. U.S. Patent and Trademark Office.*