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A Review of the Role of Artificial Neural Networks in Optimizing Laser-Processed Materials

Ikhlas Jabbar Lafta[1], M.S. Salim[2], Naseer Sabri[3]
[1]School of Laser & Optical Elect. Engineering, Al-Nahrain University, IRAQ
[2]School of Electronic & Communication Engineering, Al-Nahrain University, IRAQ
[3]School of Communication Technical Eng., Technical Engineering College, Alfarahidi University, IRAQ
muhsabri1967@yahoo.com

Abstract

The laser processing technique (LPT) as an efficient tool for material processing 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 artificial intelligence techniques-based laser process, including cutting, grooving, turning, milling, and drilling. The non-linear behavior of the material processing process using laser is a difficult and complex matter in the formation of the mathematical model of the process. Neural network techniques use experimental results and current knowledge to model, optimize, monitor, and control the laser processing process. In this paper, the applications of artificial intelligence techniques, including artificial neural networks (ANN), in modeling and optimizing the processing quality properties of laser materials are reviewed. It has been shown that artificial neural network techniques are successfully able to predict and improve the features of a laser-operated workpiece. It is also proven that AI can be used as a powerful tool for obtaining a comprehensive model and optimal setting parameters for a laser material processing process.

Keywords: Laser processing; Mathematical modeling; ANN; Optimization techniques.

1. Introduction

Lasers are very important in the recent applications mainly in the scientific purpose, and in saving the life as well as from threatening or fatal causes. Many main interesting from using laser applications is related to many advantages at the output, such as coherence and spectral purity interferometry, low divergence, velocity and distance assessment, contamination detection, and so on, or a a mix of the (metrology, communication, holography). So, in recent decades, a steward of lasers has been created that can link large species of wavelength, energy, spectral/temporal dispersion, and efficiency.

The extreme heat that a laser can create on solid materials allows for some novel, cost-effective, and rapid handling of materials that are more productive, efficient, and high-quality than previous methods. There are many advantages of utilization laser of materials treatment, that are Greater productivity, automating merit, no-contact treatment, no-finishing action, cost-effective processing, improved product standard, increased use of resources, and reduced heating impacted region. Figure 1 depicts a broad categorization of laser materials processing techniques. Generally, laser applications in processing of materials may be divided into two categories:

(a) Activities that need limited amounts of energy and power and do not require a significant change in phase or condition.

(b) To accomplish the phase change, applications needed a significant quantity of energy.

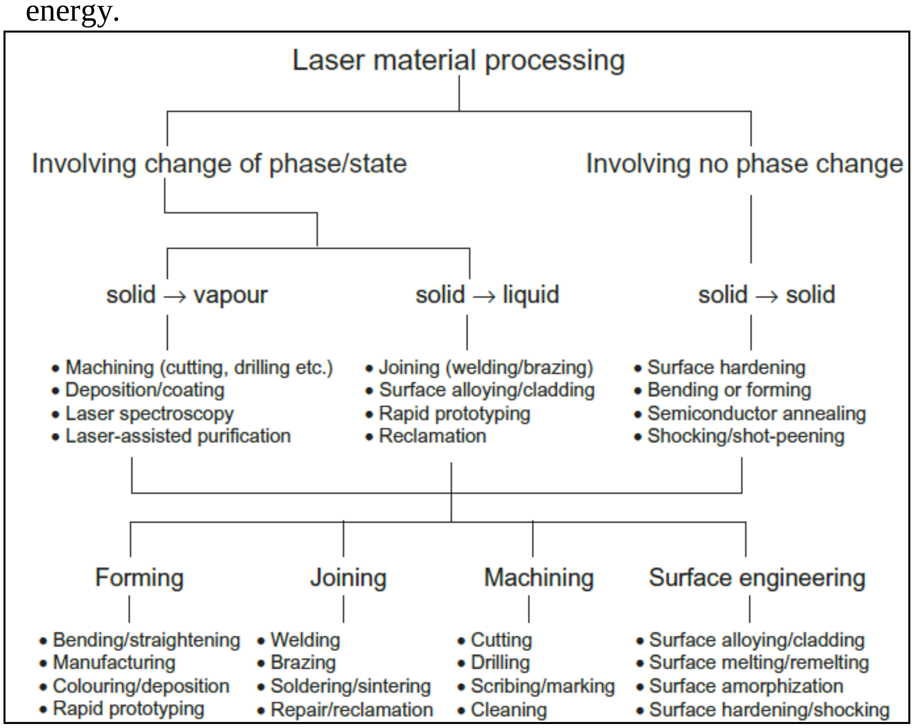

Figure 1.1: Laser material treatment classification.[1]

Polymer treatment, semiconductor drills and heat, put labeling, and writing on integrated circuit substrate, for example, are all part of the first category. While the heat treatments, welding, cutting, fusing, and glazing are examples of the second kind of application. Both effectiveness and power level of lasers are not significant in the preceding group since there is no change in phase.

The field of dissimilar laser substantial processing methods are alienated into three main types as a function of processing time, and the power of laser, which counting: only heating, melting, and vaporizing. Obviously, the interaction period and the laser power density are determined in every technique in which the concerned material subject to the required heating degree, and phase change [2-5]. Clearly, the alteration of toughening, and control in magnetic field that depending on the heating of the surface avoiding melting of the surface, and require little power density. While glazing, surface melting, cladding, and welding that entail melting, on the other hand, need a high-power density. Likewise, the drilling, cutting, and automation operation eliminate the material as vapor, subsequently, required high power density through interaction/ of a very small pulse duration. Consider the solitary standard parameter such as power density (power density multiplied by time, J/mm2) more benefit in measure the various operations with using laser. However, this practice not suitable because the specific composition of energy and time (instead of its producer) only may be got to the required thermal and physical effect.

2. Artificial intelligence

Numerous data infilling methods have indeed been widely used, including ANNs, stochastic models, and regression methods. However, ANNs, a method that expresses non-linear mappings between variables, works with incomplete data, and doesn't need assumptions about variables (French et al., 1992). As a result, the ANN method utilized in industrial and agricultural sectors benefitted many applications.[6]

3. optimizing laser-processed materials using ANN

A research team led by **A. Sharifi and A. Mohebbi (2012)** offers an alternate method based on ANNs to estimate the average droplet size in Venturi scrubbers over a broad variety of operational parameters. The ANNs were created using experimental data. The Sauter mean diameter (D32) was used as the target value, while the throat gas velocity (Vgth) with the ratio of liquid to gas (L/G) were used as input factors. The network was built using back-propagation learning techniques, and the optimal strategy was discovered. The weights of the network were then used to create a new formula for D32 prediction. This method calculates average droplet size in Venturi scrubbers better than Nukiyama, Tanasawa's correlations (1938) and Boll et al. (1974).[7]

Dhupal et al. (2009) created a five-level central composite design based on an experiment. They looked at how pulse width, pulse frequency, lamp current, cutting speed, support gas pressure affected the superiority of laser produced micro grooves. They used a feed-forward ANN method to build a prediction model for laser turning process parameters using investigational observation data based on RSM. The RSM-based optimization issue was created and solved using a multi objective genetic algorithm (GA). It was stated that using a neural network and a genetic algorithm to determine the best parameter value for a particular laser micro-turning condition in ceramic materials may be very efficient. For achieving the predicted minimum deviation of higher width of 0.0101 mm, minor width of 0.0098 mm, and depth of 0.0069 mm of laser turned micro-grooves, the best process parameter conditions were cutting pulse frequency of 3.2 kHz, speed of 22 rpm, pulse width of 6 percent duty cycle, lamp current of 19 A, and support air pressure of 0.13 N/mm2.[8]

Tsai et al. (2008) used a several regression investigation and an artificial neural network to create a prediction model for cutting Quad Flat Non-lead (QFN) packages by means of a Diode Pumped Solid State Laser. Three input variables are used in the prediction model: current, speed of cutting, and frequency.

For copper-compounded epoxy and epoxy, the cutting characteristics are (widths HAZ, depths of the cutting line, and cutting line). The ANN model was demonstrated to have the capacity to predict the laser-cutting characteristics of QFN packages. Finally, a genetic algorithm (GA) is used to determine the optimum cutting parameters that result in the smallest HAZ width and the fastest cutting speed while cutting completely. The best settings were stated to be 29 A current, 2.7 kHz frequency, and 3.49 mm/s cutting speed. [9]

The impact of laser cutting parameters such as Gas Pressure, Cutting Speed, and Laser Power on the HAZ parameter response was investigated by Pathik Patel et al. in 2016. The Taguchi L27 Orthogonal array was used to optimize the process parameters, their combinations, levels, and then predictive models were built using Second Order Regression and ANN forming methods. The relative impact of process factors on HAZ is then determined using Analysis of Variance (ANOVA). The ANN model exhibits superior settlement for HAZ prediction with accuracy more than 97% for the specified series of input parameters after comparing simulated and experimental data.[10,11]

The study team of G. Casalino et al. (2016) used ANN to examine the major impacts of development factors on the quality of welding based lase laser process. The analysis was carried out using a high brightness Yb fiber laser. In a butt arrangement, complete penetration autogenous welding of 6 mm thick AA5754 aluminum alloy sheets is accomplished. The experimental plan adjusted the welding speed and shielding gas. Visual inspection of the bead appearance was used to assess the procedure quality. Neural Tools (Excel add-in) — Palisade Corporation® developed the ANN modeling code. The statistical estimates showed a link between process factors and weld shape, allowing for a better knowledge of the welding process. Finally, the use of ANN forming for improving manufacturing process quality was shown.[12-14]

To characterize the tactile comfort of next-to-skin products, objective and subjective assessments of the handling of textile materials are critical. The usefulness of adaptive neuro-fuzzy inference system (ANFIS) and ANN modeling methods for the estimation of psychological impressions of functional textiles from mechanical characteristics was studied by the Tadesse M. G. et al. research team. Using tactile and comfort-based fabric touch characteristics, six different functional textiles were assessed using human participants for their tactile score and total hand values (THV). Then, using KES-FB, the mechanical characteristics of the similar set of examples were measured. The RMSE values for ANN and ANFIS predictions were 0.014 and 0.0122, respectively, which are much lower than the changes in perception scores of 0.85 and 0.644 for ANFIS and ANN, with less prediction mistakes. The findings show that the anticipated tangible score and THV are nearly identical to the real output acquired via human assessment. As a result, fabric objective measuring technology offers dependable measurement methods for functional fabric control, design specification, and quality inspection.[15]

4. Conclusion

In this paper, the role of neural networks in industry and materials processing, in general, is reviewed. Neural networks' human-like attributes and ability to complete tasks in infinite permutations and combinations make them uniquely suited to today's big data-based applications. Because neural networks also have the unique capacity to make sense of ambiguous, contradictory, or incomplete data, they are able to use controlled processes when no exact models are available. With the human-like ability to problem-solve — and apply that skill to huge datasets — neural networks possess the following powerful attributes such as adaptive learning, self-organization, real-time operation, prognosis, and fault tolerance. This ability is especially useful in space exploration, where the failure of electronic devices is always a possibility.

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