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Review

Computational intelligence for smart laser materials processing

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ABSTRACT

Computational intelligence (CI) involves using a computer algorithm to capture hidden knowledge from data and to use them for training "intelligent machine" to make complex decisions without human intervention. As simulation is becoming more prevalent from design and planning to manufacturing and operations, laser material processing can also benefit from computer generating knowledge through soft computing.

This work is a review of the state-of-the-art on the methodology and applications of CI in laser materials processing (LMP), which is nowadays receiving increasing interest from world class manufacturers and 4.0 industry. The focus is on the methods that have been proven effective and robust in solving several problems in welding, cutting, drilling, surface treating and additive manufacturing using the laser beam.

After a basic description of the most common computational intelligences employed in manufacturing, four sections, namely, laser joining, machining, surface, and additive covered the most recent applications in the already extensive literature regarding the CI in LMP. Eventually, emerging trends and future challenges were identified and discussed.

Contents

1. Lasers in manufacturing processes

Since the early industrial applications, which have focused on processes such as welding, machining, and heat treatment, the laser materials processing has evolved and included laser forming, shock peening, laser additive fabrication, micromachining, and nanoprocessing [1]. New opportunities for the application of lasers in materials processing have been following the development of new high-power laser sources with new wavelengths such as semiconductor lasers (800–1000 nm), Neodymium doped YAG (Nd: YAG) lasers (1064 nm) and Excimer (126–351 nm). The laser power increases steadily whereas the power consumption of laser systems decreases. The ability to move the laser focus very quick over the work piece surface has improved the performance and

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accuracy and many laser manufacturing processes have been improved (e.g. laser-welding, forming, hardening, prototyping, lithography) [2]. Therefore, lasers have proved to be versatile and have reached a growing success among the world class manufacturers.

All laser material processing operations can be controlled by an appropriate combination of power density and interaction time. Those processes are divided into three major classes, namely, heating without melting or vaporizing like in surface hardening, melting without vaporizing like in cladding and vaporizing like in cutting [3]. Many process parameters play major roles in design and realization of a laser manufactured product. The working conditions can affect the laser machine performance, the beam stability, and the operation precision and repeatability. Given the complexity of handling the laser material interaction in an industrial site, the computer has gained a leading position in conduction, correction, and optimization of every laser application to manufacturing. Soft computing is becoming the leading tool for engineering systems handling. In the case of laser systems, it can be exploited for the selection of process parameters and monitoring that are required to achieve the desired results in terms of processing speed, efficiency, quality and reproducibility.

Computational intelligence represents a large growing slice of soft computing techniques. They are consolidated tools for modeling, characterization, and forecasting in material engineering [4]. The most used but not limited-to CIs are artificial neural network (ANN), genetic algorithm (GA), fuzzy logic (FL), metaheuristic methods. They are highly result oriented, smarter, useful and less expensive than conventional computational techniques.

They can help solving out problems entangled with process investigation, modeling, optimization, and control, also in collaboration with statistics, numerical and analytical tools. Among numerical methods, Finite element method (FEM) is one of the most popular methods in solving partial differential equations (PDEs) governing domains with irregular geometries. While highly accurate, FEM can be computationally slow when applied to complex problems like laser materials interaction. The application of existing models of computation from the artificial intelligence community, however, can greatly simplify program development, ease the burden of maintenance, and result in a more robust system. There are several applications in the field of manufacturing that demonstrate the synergy between the two numerical techniques [5–7].

Statistical approach is a general term governing the application of a statistical model in the selected field in which it revolves a probability distribution built to facilitate deductions made from available data. A basic statistical approach is based on the design of experiment [8]. Hybrid CI-statistics design strategy for the determination of the optimum laser parameters which simultaneously meets the requirements for several quality characteristics can be determined. The optimal parameter settings that yield the maximal synthetic performance measure can be determined [9].

The applications covered in this paper group into four sections, namely, laser joining, laser machining and micromachining, laser surfacing engineering, and laser prototyping and additive. Besides briefly discussing the scope and principle of these processes, each section gives a picture of the most recent references related with the application of CI to laser materials processing (LMP).

Finally, the emerging trends and future challenges in the application of CI simulation to LMP were identified and discussed.

2. Computational intelligence (CI)

The use of computers for better understanding and interpretation of processes is spread through human activities so are the computational intelligences. This paragraph provides a brief description of the computational intelligences that were used in the laser materials processing that are collected in this paper. Those CI are just a part of the large world of available intelligent algorithms. However, it is reasonable to limit the survey to artificial neural networks, fuzzy logic and adaptive neuro-fuzzy (ANF), metaheuristic techniques.

2.1. Artificial neural networks

Artificial neural networks (ANN) are the most popular artificial learning tool in computer science and other research disciplines. These systems are self-learning and trained, rather than explicitly programmed, and excel in areas where the solution or feature detection is difficult to express in a traditional computer program.

They act like a biological brain whose basic unit is the neuron. Each neural unit links many others, and it can enhance or inhibit the activation state of adjoining neural units. Each individual neural unit computes using summation function (Σ) the weighted (w) signal (x) coming from the unit ahead. There may be a threshold function or limiting function on each connection and on the unit (bias) such that the signal must surpass the limit before propagating to other neurons (y) (Fig. 1).

The computational neural units are stored in layers so the signal path traverses from the first (input), to the last (output) layer of neural units. Neural networks typically consist of multiple layers and the signal path traverses from the first (input), to the last (output) layer of neural units (Fig. 2).

The weights (ws) of classical neural network are calculated during the training phase. In that phase a forward stimulus, which can be the process parameters, is elaborated from the input layer and

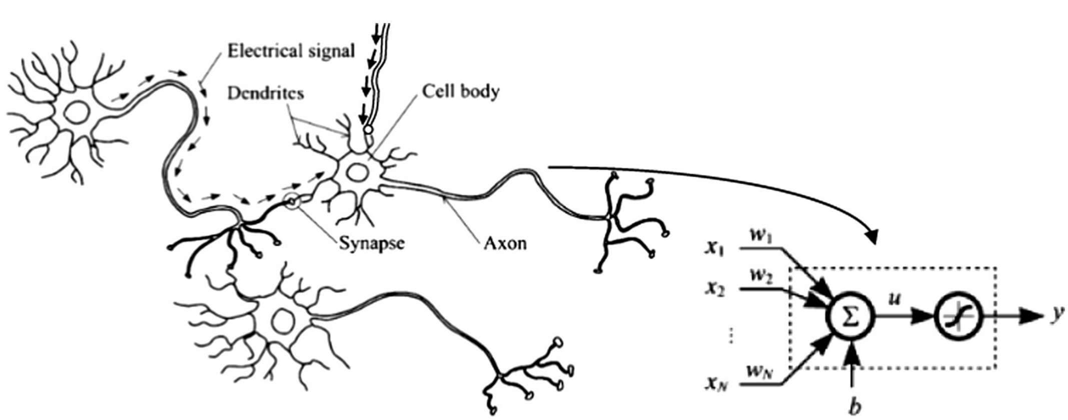

Fig. 1. Biological neurons representation (left) and mathematical model (right).