Biomimetic methods and AI technics assisting Heat Treatment processes

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In the last decade several computational methods have been applied successfully to optimize the heat treatment processes. Among others, Biomimetic methods have been developed for solving complex and robust optimization problems on the field of casting, metal forming and heat treatment operations. These numerical methods are based on the emulation of the models, systems, and elements of nature for the purpose of solving complex human problems. These models have been inspired by structures and behavior of living creatures. The development of computer modeling and simulation tools have led to great advances in understanding how materials behave during Heat Treatment operations. Unfortunately, high-fidelity computational simulations can take significant time to run and require large computational capacity. Process optimization requiring many simulations at different conditions can be expensive. To mitigate these obstacles to widespread use of sophisticated computer models, Artificial Intelligence methods based on neural networks could be support the Heat Treatment processes.

Keywords: *Artificial Intelligence , Machine Learning, Biomimetics, Swarm optimization, Heat Treatment*

1. Introduction

Nature has always been the source of inspirations for scientists and engineers to solve problems in various fields. Abundant instructive heat and mass transfer enhancement phenomena as well as surface related mechanisms are observed in nature, partially imitated and applied to enhance heat transfer and surface technology in engineering. Today's manufacturing industry is witnessing a significant surge in the volume of available data. Substantial data is continuously gathered throughout the entire production process, hailing from an array of sources, including sensors, machinery, and other data collection mechanisms [1]. This data, particularly that related to product quality, holds the potential to enhance quality control and monitoring processes. In line with the European Commission's vision of "factories of the future," manufacturers are compelled to confront heightened competition from global rivals. One of the strategic responses to this challenge involves the integration of innovative technologies, services, and applications .

The pivotal elements in this transformation lie in the extraction, management, and analysis of data. Thus, it is not only the development of machine learning (ML) algorithms that assumes significance but also the efficient implementation of orchestration procedures, which encompass the entire spectrum from raw process data to the deployment of a model [2]. This orchestration is often referred to as an artificial intelligence (AI) pipeline. ML plays an essential role in addressing the contemporary manufacturing hurdles that are posed by extensive and intricate data, given that raw process data lacks inherent information[3]. A pragmatic approach to resolving these challenges is founded on the utilization of both qualitative and quantitative methodologies, enabled by suitable tools for data ingestion, storage, and processing, facilitating ML and the discovery of novel insights. As emphasized by Wuest et al. [4], data-driven solutions excel at identifying nonlinear relationships by transforming raw data into feature spaces, often referred to as models. These models can subsequently be applied to a variety of tasks encompassing forecasting, regression, prediction, detection, and classification. ML is an advanced way of processing data to get deeper insights. Various kinds of ML techniques can uncover non-linear and overly complex patterns in several types of data [4]. One general possibility of ML techniques is the ability of handling advanced problems that often occur in modern production environments[5]. These problems can be solved with troubleshooting, control and optimization where the ML models [6] play a huge role in finding solutions [18]. ML is applicable in several perspectives of manufacturing which all play a significant role in daily business operations. It can result in a competitive position on the market, reducing production costs and limiting environmental impacts [7], [8]. Companies can innovate in manufacturing efficiency by more advanced process control and forecasting maintenance. By enabling better data insights through ML, industries can reduce waste, energy usage and carbon emissions. Products can also be more reliable manufactured and sold with increased quality [7]. To increase ML's potential in manufacturing, the flow of data can be orchestrated in an AI pipeline, which accelerates the process of taking raw data to tuned ML models.

2. Artificial Intelligence approach in Heat Treatment

The techniques of AI applied successfully in Heat Treatment and Surface Engineering is presented in the following section.

2.1 Machine Learning

Machine learning (ML) represents a subset of computational AI techniques [9], [10] that has gained widespread adoption across various domains, including the realm of heat transfer modeling [11], [12]. Within the realm

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of heat transfer research, ML methods are harnessed to sift through the vast volumes of data arising from experiments, field observations, and simulations[13]. Through the utilization of ML-driven data analysis, researchers can enhance the speed and precision with which they interpret fluid dynamics and forecast quantitative flow characteristics based on empirical data[13]. Consequently, the use of ML techniques has witnessed a surge in popularity in the field of heat transfer research [14]. In sum, ML techniques have exhibited significant potential for bolstering the efficiency and accuracy of data analysis within the domain of heat transfer research, and further exploration of these methodologies promises substantial advancements in the field [15].

2.2 AI in steel manufacturing

The complexity of the steelmaking process and the numerous production chains generating process data make this industry an ideal candidate for AI research and implementation advancements [16]. The integration of data with cutting-edge information technologies forms the nucleus of future smart factories, spurring extensive research in the realms of steel manufacturing and process enhancements [3]. According to Wuest et al. [4], neither the steelmaking sector nor the broader manufacturing industry has fully embraced or adopted cloud computing architectures and applications, partly due to the challenges of transitioning them to a production-ready state. Pellegrini et al. [3]conducted research centered on the implementation of a pipeline concept for various AI-applicable processes, setting the stage for the next generation of manufacturing. The research is built on a machine learning-adaptable architecture that supports cloud modules for extracting features from diverse sources of raw data, standardizing their storage, and facilitating horizontal and vertical scalability. This architecture also accommodates data mining and visualization for predictive and monitoring purposes. Throughout their research, Pellegrini et al. present three distinct use cases for this architecture to demonstrate its value in steel manufacturing. Firstly, it serves as a decision support tool for operators, making binary classification predictions about the probability of clogging during continuous casting. Secondly, it offers real-time monitoring of steel temperature during the degassing process. Lastly, it employs deep learning for image recognition to detect surface defects. Pellegrini et al. conclude that one of the main advantages of the cloud-based architecture is its capacity to handle resource-intensive tasks, such as image processing, while reducing initial hardware costs. The results indicate that this architecture has numerous other application areas and can deliver immediate improvements in industry precision and operational costs. Cemernek et al. [17] investigated current machine learning techniques for the continuous casting process of steel through an extensive review of existing literature. Their findings suggest that predicting steel quality and defects requires a comprehensive understanding of the entire process, with decision trees and neural networks forming the foundation for the most applicable algorithms. When predicting quality, a broader range of target variables may be involved, as quality encompasses distinct characteristics like hardness and tensile strength. As a result, quality prediction research exhibits greater diversity in its models and applications, given that different variables are relevant for different quality measures. The research concludes that supervised and active learning could be highly beneficial in the steel industry, particularly if new techniques are introduced to handle imbalanced data [17].

Quality enhancement in steel manufacturing has been the focus of extensive research, with surface defect detection emerging as one of the most common applications of machine learning in the steel industry [3]. Published studies exploring AI in heat treatment processes often aim to develop systems that mimic human behavior in real-time or offer decision support functions for processes involving human inspection to detect defects [18]. Many of these studies rely on image processing algorithms [19], while others are based on mathematical correlations between input parameters and known output quality parameters, all stored in a knowledge base [18]. For instance, Mitra et al. [18] investigates furnace temperature, material thickness, weight, and steel grade to predict furnace temperature for achieving optimal final carbon content, hardness, ductility, formability, and tensile strength. Other research, such as that conducted by Tsutsui et al.[20], Panda et al. [21], and DeCost et al. [22], examines the physical attributes of steel and employs control parameters extracted from sensors like images or processing data for temperature and time inside the furnace. Previous studies take into account the material's composition and its predicted mechanical properties to determine optimal recipes for the heat treatment process. These studies rely not only on collected process data but also on data specifying how the steel's characteristics should be scientifically managed [20].

2.3 Heat treatment analysis for quality improvement

The common objective in research concerning heat treatment is to utilize deep neural networks or linear regression to create predictive models and methodologies for general steel products [23]. For instance, Carneiro et al.'s research, like this thesis, explores the prediction of quality outcomes to minimize production line bottlenecks, such as quality tests. Carneiro et al. investigates steel tubes using neural networks and tree ensemble methods in the context of water-quenched steel, adopting an unsupervised approach. Their research sets itself apart from previous studies by delving into a process that incorporates data from a quenching tank, while analyzing the effects of water flow and pressure on product quality. The findings underscore the importance of investigating machine learning techniques in tandem with variable selection for each unique use case. This is necessary because various quality parameters, such as tensile strength, hardness, and yield strength, are influenced by different input variables and ultimately predicted by different algorithms [24].

Another study that predicts quality, focusing on yield strength and tensile strength, is the work of Xie et al. [25], who apply deep learning to raw steel parameters and process data from the reheat furnace process, rolling data, and water-cooling data at a steel plant. The cooling data encompasses measurements like average cooling rate, start and finish cooling temperature, encompassing temperatures between 200 and 900 degrees Celsius. The study comprises 27 input parameters, and the deep learning model achieves an accuracy of 0.907. This research results in the deployment of the model online at an industrial site, featuring a graphical user interface to aid operators in managing hot roll process parameters through predictive analysis [25].

Hanza et al. [26] predict the total hardness of steel after continuous cooling, employing Artificial Neural Networks. Their investigation explores whether chemical composition can be replaced as input variables by the Jominy distance. The Jominy distance value is closely linked to a material's composition and its capacity to harden. These values can be calculated using a formula based on steel hardness with a microstructure of 50% martensite. Two tests are conducted, one involving chemical compositions and the other featuring the Jominy distance value. The research reveals that input data for heat treatment temperature, heating time, cooling time down to 500C, and the Jominy distance can yield nearly as accurate results in predicting total hardness compared to models that include chemical composition. Based on this, Hanza et al.[26] conclude that only four input variables are needed to predict hardness, simplifying the model's complexity.

A combination of Artificial Neural Networks and Finite Element Method have been used to predict HTC in the water quench process of large size forged steel blocks[27]. Using this method the wetting kinetics process during water quenching have been estimated on a high level of accuracy.

For the explanation of hardness alterations of a component made from the grade 18CrNi8 has been investigated by traditional physical models and data-driven machine learning models [27]. The prediction of hardness on cylinder heads made of 100Cr6 based on process has been performed by using AI apparatus [28]. Predictive maintenance based on massive data processing of process data has been developed for Industrial Heat Treatment operations [29], [30].

2.4 Machine Learning for Additive Manufacturing Process

The ML has been widely applied in the deployment of AM technologies. The applicability and efficiency of the AI approach in an AM process are dependent on the type of process, and the relevant design features such as material condition, process operation, part and process design, and the working environment; all these factors will be considered during the analysis [31]. Gardan and Schneider [32] conducted an optimization of the orientation, construction, design of the parts and parameters, and material. The standard techniques of AI used in rapid prototyping[33].

Within the domain of AM processes, ML is applied in two main areas: parameter optimization and process monitoring. Process parameter optimization is often a manual and time-consuming process, making it costly. Since manual parameter optimization requires the production of large numbers of samples, there is readily available data for the production of ML tools. Said tools, which make up a plurality of the research on ML for AM[34], largely take the route of optimizing key parameters for a particular quality indicator or set of indicators [35].

The porosity is the leading quality indicator in several research, Liu et al. [36] built on a "physics-informed" model rather than a conventional "setting" model. The novel "physics-informed" model was identified as being more easily generalized to other machines, although this was not tested. A key area for optimization in material extrusion is component surface roughness [37]. Li et al. [38]built a predictive model for surface roughness based on build plate and extruder temperature, build plate and extruder vibration, and melt pool temperature.

More recent works have studied the properties of the final part: Narayana et al. [39] built an ANN (Artificial Nureal Network) to predict built part height and density from laser power, scan speed, powder feed rate, and layer thickness. It was found that these parameters were all of significant importance for density whereas scan speed and feed rate had the largest effect on build height. These findings were reinforced by the model's prediction accuracy of 99%. Xia et al.[40], used an NN to model and predict surface roughness based on overlap ratio, welding speed, and wire feed speed with a root mean square error of 6.94%. A small training set was identified as a major limiter on the model's accuracy [40].

While parameter optimization may help to improve process predictability, it cannot eliminate failures entirely[41]. With print failures contributing significantly to the cost of

AM parts [42], process monitoring techniques able to detect build failures and defects are necessary. Various ML implementations have sought to solve this problem and fall into two categories depending on their input data type: optical and acoustic. Optical monitoring solutions are the most widely used, with the data often coming from digital, high speed, or infrared cameras[35]. In PBF processes, where the bulk of monitoring research is currently concentrated, the most common target of these computer vision tasks is the melt pool.

Quality control of AM processes has a significant role in automated production and therefore several methods have been suggested. Some of them are based on continuous camera observation and image analysis. The contour of each printed layer is compared with the desired geometry by using metrics generated from the image of the manufactures layer.

The metrics are assumed to represent the gemoterical match of these two images. The less the similarity, the higher the probability that the printing process has failed. The procedure to obtain this layer-wise distance metrics based on the following steps:

1.) creating binary section cut images

2.) creating binary layer photos

3.) comparison of the images

In addition to, several images recorded on malfunction of AM process have been used to train the ML algorithm in order to recognize the failed production. From thermal data of the melt pool, Kwon et al. [41]trained a CNN-based program to differentiate between high, medium, and low quality builds with a failure rate of under 1.1%, allowing for potential time and cost savings. Other works have used optical data from laser melting plumes [43], [44] for similar quality classification tasks, with Zhang et al. [43], [44]finding that the best results are achieved when melt pool, plume, and spatter data are used together to classify part quality. The most recent work found a type of NN called a long–short term memory network, to be most effective in prediction, with a root mean squared error of 13.9% [43].

3. The Biomimetic concept in Heat Treatment

The increasing interest in applying biological inspired approach (biomimetics) to real engineering problems lies in the fact that the apparently simple structures and organizations in nature are capable of dealing with most complex systems and tasks with relative ease. Nature offers lots of micro/nano-scale hierarchical structures with remarkable efficiency for tailored functionalities. Previous studies found that the bio-inspired hierarchical structures like lotus leaf structure on implants could increase cell contact with the structures, providing more appropriate spaces for cell proliferation and differentiation [45], [46]. Design of metamaterials are also supported by Bioinspired structures. The examples of bio-inspired metamaterials are honeycomb, gyroid which is one of the triply periodic minimal surfaces and is also discovered in butterfly wings scale[47]. Similarly diamond metamaterial is found in the exoskeletons of the beetles[48]. Recently, hierarchical architecture of the bird feathers is also used to model superior mechanical performance than the honeycombs [49].

Beside the applications of biomimetic methods in structural design of new materials the nature-inspired algorithms for optimization of complex problems came to the forefront of interest. Compared to classical optimization techniques which aim at exact optimal solutions, bio-inspired (heuristic) search methods propose instead to locate the near optimal solutions and do not rely on availability of analytical models. The flexible structure of such a search mechanism can not only handle different knowledge representations in a single framework, but can also provide pragmatic solutions in a more efficient way.

By far the majority of nature-inspired algorithms are based on some successful characteristics of biological system. Therefore, the largest fraction of nature-inspired algorithms are biology-inspired, or bio-inspired for short. Among bio-inspired algorithms, a special class of algorithms have been developed by drawing inspiration from swarm intelligence. Therefore, some of the bioinspired algorithms can be called swarm-intelligence based. In fact, algorithms [50] based on swarm intelligence are among the most popular. Good examples are ant colony optimization [51], the particle swarm optimization (PSO) [52], cuckoo search [53], bat algorithm [54], firefly algorithm [55], grey wolf optimizer [56].

The PSO approach has been applied to predict the HTC as a function of surface temperature and local coordinate heat transfer process during immersion quenching of a cylindrical specimen [57]. A stainless-steel rod was equipped by 8 thermocouples, which are mounted 1 mm below the surface and at different distances from the bottom of the cylinder. The cooling curves recorded during immersion quenching in water were applied to estimate the temporo-spatial heat HTC. In addition, the characterization of heat extraction conditions, as well as wetting kinetics, can be performed much faster (less computational efforts) by using graphic accelerator cards and bio-inspired algorithms [58]

4. Summary

The Artificial Intelligence approaches and Biomimetic methods supporting heat Treatment processes have been shortly discussed in this review. These computational techniques greatly contribute to the future heat treatment technology being based on new materials, new solutions and optimized production processes.

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