Artificial Intelligence Techniques and Biomimetic Methods Supporting Heat Treatment Processes

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Abstract: 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: keyword1; Biomimetics; Swarm intelligence; PSO; FWA; GA; NSGA; Machine Learning; Artificial Intelligence; Heat Treatemtn; Additive manufacturing

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) is a subset of computational AI methods that has been widely embraced [10] across various fields, including heat transfer simulations [11, 12]. In heat transfer research, ML techniques play a crucial role in managing extensive datasets from experiments, field observations, and simulations. By employing ML-driven data analysis, researchers can expedite and refine the interpretation of fluid dynamics [13] and predict flow characteristics based on empirical evidence. Consequently, ML approaches have become increasingly popular [14] in the heat transfer research community. Overall, ML methods show significant potential in enhancing the efficiency and accuracy of data analysis in heat transfer research [15]. Further exploration of these methodologies is poised to bring about substantial advancements in the field, indicating a promising trajectory for future research endeavors.

2.2 AI in Steel Manufacturing

The steelmaking process's complexity, coupled with the multitude of production chains generating process data, positions this industry as an ideal candidate for advancements in AI research and implementation [16]. The convergence of data with state-of-the-art information technologies lies at the core of future smart factories, driving extensive exploration in steel manufacturing and process improvements [3]. However, as highlighted by Wuest et al. [4], neither the steelmaking sector nor the broader manufacturing industry has fully embraced cloud computing architectures and applications, partly due to the challenges in transitioning them to a production-ready state.

Pellegrini et al. [3] conducted research focused on implementing a pipeline concept for various AI-applicable processes, laying the groundwork for the next manufacturing era. Their work revolves around a machine learning-adaptable architecture supporting cloud modules for feature extraction from diverse raw data sources, standardizing storage, and enabling horizontal and vertical scalability. Additionally, the architecture facilitates data mining and visualization for predictive and monitoring purposes.

Throughout their study, Pellegrini et al. illustrate three distinct use cases for this architecture within steel manufacturing. Firstly, it acts as a decision support tool for operators, making binary classification predictions regarding the probability of clogging during continuous casting. Secondly, it enables real-time monitoring of steel temperature during the degassing process. Lastly, it employs deep learning for image recognition to detect surface defects. The researchers highlight one of the main advantages of the cloud-based architecture – its capability to handle resource-intensive tasks, like image processing, while reducing initial hardware costs. The findings suggest that this architecture holds potential across various application areas and can immediately enhance industry precision and operational efficiency. Cemernek et al. [17] explored current machine learning techniques for the continuous casting process of steel through a comprehensive literature review. Their analysis indicates that predicting steel quality and defects necessitates a thorough understanding of the entire process, with decision trees and neural networks serving as foundational algorithms. Quality prediction research displays diversity in models and applications due to the involvement of various target variables, such as hardness and tensile strength. The researchers suggest that supervised and active learning, coupled with new techniques to handle imbalanced data, could significantly benefit the steel industry.

Extensive research efforts have been directed towards enhancing the quality of steel manufacturing, with particular emphasis on surface defect detection, which stands out as a prevalent application of machine learning within the steel industry [3]. Numerous published studies delve into the integration of AI in heat treatment processes, often aiming to develop systems that emulate human behavior in real-time or provide decision support for processes involving human inspection to identify defects [18]. Many of these studies leverage image processing algorithms [19], while others rely on mathematical correlations between input parameters and established output quality parameters stored in a knowledge base [18].

For instance, Mitra et al. [18] delve into factors like furnace temperature, material thickness, weight, and steel grade to forecast furnace temperature, crucial for achieving optimal final carbon content, hardness, ductility, formability, and tensile strength. Similarly, research by Tsutsui et al. [20], Panda et al. [21], and DeCost et al. [22] examines the physical attributes of steel and utilizes control parameters extracted from sensors, such as images or processing data related to temperature and time within the furnace. Previous studies meticulously consider the material's composition and its predicted mechanical properties to devise optimal recipes for the heat treatment process. These endeavors draw not only from collected process data but also from data outlining scientifically sound practices for managing the steel's characteristics [20].

2.3 Heat Treatment Analysis for Quality Improvement

Research focused on heat treatment commonly aims to develop predictive models and methodologies for general steel products using deep neural networks or linear regression [23]. For example, Carneiro et al.'s study, akin to this thesis, delves into predicting quality outcomes to mitigate production line bottlenecks, such as quality tests. Carneiro et al. examine steel tubes using neural networks and tree ensemble methods within the context of water-quenched steel, employing an unsupervised approach. Their research stands out by exploring a process that incorporates data from a quenching tank while analyzing the impacts of water flow and pressure on product quality. The findings underscore the significance of exploring machine learning techniques alongside variable selection for each specific use case. This is crucial as various quality parameters, including tensile strength, hardness, and yield strength, are influenced by different input variables and are ultimately predicted by different algorithms [24].

Another study, focusing on predicting quality metrics like yield strength and tensile strength, is conducted by Xie et al. [25]. They utilize deep learning techniques on raw steel parameters and process data from the reheat furnace process, rolling data, and water-cooling data at a steel plant. The cooling data comprises measurements such as average cooling rate, start and finish cooling temperature, covering temperatures ranging from 200 to 900 degrees Celsius. With 27 input parameters, the deep learning model achieves an accuracy of 0.907. The outcome of this research leads to the deployment of the model online at an industrial site, featuring a graphical user interface to assist operators in managing hot roll process parameters through predictive analysis [25].

Hanza et al. [26] utilize Artificial Neural Networks to predict the total hardness of steel post continuous cooling, exploring the substitution of chemical composition with the Jominy distance as input variables. The Jominy distance, closely linked to a material's composition and its hardening capacity, can be calculated based on a formula derived from steel hardness with a microstructure of 50% martensite. Two tests are conducted: one involving chemical compositions and the other the Jominy distance value. Results reveal that input data for heat treatment temperature, heating time, cooling time down to 500°C, and the Jominy distance can yield nearly as accurate predictions of total hardness as models incorporating chemical composition. Consequently, Hanza et al. [26] conclude that only four input variables are necessary for hardness prediction, simplifying the model's complexity.

A fusion of Artificial Neural Networks and the Finite Element Method has been employed to forecast Heat Transfer Coefficient (HTC) in the water quenching process of large forged steel blocks [27]. This approach enables precise estimation of the wetting kinetics process during water quenching. For understanding hardness alterations in a component made from grade 18CrNi8, investigations have been conducted using both traditional physical models and data-driven machine learning models [27]. Similarly, predictive maintenance for Industrial Heat Treatment operations has been developed based on extensive processing of process data [29], [30]. Additionally, AI techniques have been applied to predict hardness on cylinder heads made of 100Cr6 based on process parameters [28].

2.4 Machine Learning for 3D Printing Process

Machine learning (ML) has found extensive application in the implementation of Additive Manufacturing (AM) technologies. The effectiveness and applicability of AI approaches in AM processes depend on various factors such as the type of process, relevant design features including material condition, process operation, part and process design, and the working environment. These factors are carefully considered during the analysis [31]. Gardan and Schneider [32] conducted an optimization study encompassing part orientation, construction, design, parameters, and materials. Standard AI techniques are commonly employed in rapid prototyping [33]. In the realm of AM processes, ML is primarily applied in two main domains: parameter optimization and process monitoring. Manual parameter optimization is often laborious and time-consuming, leading to high costs. ML tools, which constitute a significant portion of research in ML for AM, typically focus on optimizing key parameters for specific quality indicators [34].

Porosity stands out as a primary quality indicator in several studies. Liu et al. [36] developed a "physics-informed" model, which was identified as more easily generalizable to other machines, although not empirically tested. Surface roughness is a crucial area for optimization in material extrusion. Li et al. [38] constructed a predictive model for surface roughness based on various factors such as build plate and extruder temperature, vibration, and melt pool temperature. Recent research has also focused on predicting final part properties. Narayana et al. [39] utilized Artificial Neural Networks (ANN) to predict built part height and density from parameters like laser power, scan speed, powder feed rate, and layer thickness. Xia et al. [40] employed NN to model and predict surface roughness based on overlap ratio, welding speed, and wire feed speed, achieving a root mean square error of 6.94%. However, a small training set was identified as a significant limitation on the model's accuracy [40].

While parameter optimization can contribute to improving process predictability, it cannot entirely eliminate failures within Additive Manufacturing (AM) processes [41]. The occurrence of print failures significantly impacts the cost of AM parts [42], underscoring the critical need for effective process monitoring techniques capable of detecting build failures and defects. These techniques, often driven by machine learning (ML) implementations, typically fall into two categories based on their input data type: optical and acoustic. Among these, optical monitoring solutions, leveraging data from digital, high-speed, or infrared cameras, are the most prevalent [35]. Particularly in Powder Bed Fusion (PBF) processes, where much of the monitoring research is concentrated, computer vision tasks commonly target the melt pool as a key area of interest.

In the realm of AM processes, quality control assumes paramount importance in ensuring automated production processes meet stringent standards. Consequently, several monitoring methods have been proposed to enhance quality control. One notable approach involves continuous camera observation coupled with image analysis. This method entails comparing the contour of each printed layer with the desired geometry using metrics derived from layer images. Any significant dissimilarity between the two images indicates a higher likelihood of process failure. The process to obtain layer-wise distance metrics involves several steps, including creating binary section cut images, generating binary layer photos, and subsequently comparing the images.

Moreover, ML algorithms have been trained using thermal data from the melt pool to discern between high, medium, and low-quality builds with an impressively low failure rate of under 1.1% [41]. Similarly, optical data from laser melting plumes has been effectively utilized for quality classification tasks, with studies indicating that optimal results are achieved when melt pool, plume, and spatter data are combined [43], [44]. Recent advancements have witnessed the adoption of Long-Short Term Memory (LSTM) networks for prediction, demonstrating a root mean squared error of 13.9% [43]. These developments underscore the potential of ML-driven process monitoring techniques to enhance the reliability and efficiency of AM processes, thereby mitigating costs associated with print failures and defects.

3 The Biomimetic Concept in Heat Treatment

The burgeoning interest in applying biomimetic approaches to real engineering challenges stems from the recognition that seemingly simple structures and organizations found in nature are adept at handling complex systems and tasks with remarkable efficiency. Nature presents an array of micro/nano-scale hierarchical structures that offer tailored functionalities with remarkable efficiency. Previous research has shown that bio-inspired hierarchical structures, such as the lotus leaf structure on implants, can enhance cell contact with the structures, providing conducive spaces for cell proliferation and differentiation [45], [46]. The design of metamaterials is also facilitated by bioinspired structures. Examples include the honeycomb and gyroid, discovered in butterfly wings scales, and the diamond metamaterial found in beetle exoskeletons [47], [48]. More recently, the hierarchical architecture of bird feathers has been utilized to model mechanical performance superior to that of honeycombs [49].

Beyond structural design, biomimetic methods have gained prominence in optimizing complex problems. Unlike classical optimization techniques that seek exact optimal solutions, bio-inspired (heuristic) search methods aim to locate near-optimal solutions without relying on analytical models. The adaptable nature of such search mechanisms enables handling various knowledge representations within a single framework, offering pragmatic solutions more efficiently.

A significant portion of nature-inspired algorithms draws inspiration from successful biological characteristics, categorizing them as biology-inspired or bio-inspired algorithms. Among these, swarm intelligence-based algorithms hold a prominent position. Examples include ant colony optimization, particle swarm optimization (PSO), cuckoo search, bat algorithm, firefly algorithm, and grey wolf optimizer [50]-[56].

For instance, PSO has been applied to predict Heat Transfer Coefficient (HTC) as a function of surface temperature and local coordinate heat transfer process during immersion quenching of a cylindrical specimen [57]. In a study, a stainless-steel rod equipped with 8 thermocouples was immersed in water, with cooling curves recorded to estimate the temporo-spatial heat HTC. Furthermore, characterizing heat extraction conditions and wetting kinetics can be achieved more efficiently using graphic accelerator cards and bio-inspired algorithms, reducing computational efforts [58].

Conclusions

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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