Magna Scientia Advanced Research and Reviews

eISSN: 2582-9394

Cross Ref DOI: 10.30574/msarr

Journal homepage: https://magnascientiapub.com/journals/msarr/

(REVIEW ARTICLE)

Check for updates

Theoretical model for predicting microstructural evolution in superalloys under directed energy deposition (DED) Processes

Enoch Oluwadunmininu Ogunnowo [1, *], Elemele Ogu [2], Peter Ifechukwude Egbumokei [3], Ikiomoworio Nicholas Dienagha [4] and Wags Numoipiri Digitemie [5]

[1] *Department of Mechanical Engineering, McNeese State University, Louisiana, USA.*
[2] *TotalEnergies Exploration & Production Nigeria Limited.*
[3] *Shell Nigeria Gas (SEN/ SNG), Nigeria.*
[4] *Shell Petroleum Development Company, Lagos Nigeria.*
[5] *Shell Energy Nigeria PLC.*

Magna Scientia Advanced Research and Reviews, 2022, 05(01), 076–089

Publication history: Received on 10 April 2022; revised on 11 June 2022; accepted on 13 June 2022

Article DOI: https://doi.org/10.30574/msarr.2022.5.1.0040

Abstract

Directed Energy Deposition (DED) processes have emerged as a pivotal additive manufacturing technique for fabricating high-performance components using superalloys. The ability to predict microstructural evolution in these alloys during DED is critical for ensuring desired mechanical properties and structural integrity. This study presents a theoretical model for predicting the microstructural evolution of superalloys under the complex thermal and mechanical conditions inherent in DED processes. The proposed model integrates thermodynamic principles, kinetic simulations, and phase-field modeling to capture the interactions between thermal gradients, solidification dynamics, and phase transformations. Key variables include deposition parameters, cooling rates, and alloy composition, which collectively influence grain growth, dendritic structures, and precipitation behavior. By incorporating computational thermodynamics, the model enables real-time predictions of phase stability and morphology changes during deposition and solidification. Finite element analysis (FEA) is utilized to simulate the thermal cycles and stress distributions that drive microstructural changes. Additionally, the model accounts for the effects of multiple thermal cycles, such as reheating and remelting, which significantly impact grain refinement and residual stresses. Machine learning techniques are employed to refine predictions by analyzing large datasets generated from experimental and simulated results. The model is validated through experimental studies on nickel-based superalloys using advanced characterization techniques, including electron microscopy and X-ray diffraction. Results demonstrate the model's capability to accurately predict grain structure, phase distribution, and mechanical property variations, thereby providing insights into optimizing process parameters for improved material performance. This study establishes a foundational framework for understanding and controlling microstructural evolution in superalloys during DED processes. The theoretical model offers significant potential for enhancing the reliability and efficiency of additive manufacturing in industries such as aerospace, energy, and automotive, where superalloys are extensively used.

Keywords: Directed Energy Deposition; Superalloys; Microstructural Evolution; Phase-Field Modeling; Thermal Cycles; Solidification Dynamics; Finite Element Analysis; Machine Learning

1. Introduction

Directed Energy Deposition (DED) processes are a subset of additive manufacturing techniques that have gained significant attention in recent years due to their ability to fabricate complex geometries and repair damaged components. DED processes use focused thermal energy, typically from a laser, electron beam, or plasma arc, to melt

* Corresponding author: Enoch Oluwadunmininu Ogunnowo.

and fuse materials, usually metal powders or wires, onto a substrate. These processes are commonly employed in industries such as aerospace, automotive, and power generation, where the need for high-performance materials and parts is critical (Albannai, 2022, Das, 2022, Zhou, et al., 2022). Among the materials used in DED, superalloys are particularly favored for their exceptional mechanical properties, including high-temperature strength, oxidation resistance, and durability, making them ideal for applications in turbine blades, jet engines, and other high-stress, high-temperature environments (Adomako, Haghdadi & Primig, 2022).

Despite their advantages, predicting the microstructural evolution of superalloys during DED remains a significant challenge. The rapid heating and cooling cycles inherent to the DED process can lead to complex and often unpredictable microstructural changes, such as phase transformations, grain size variation, and precipitation of secondary phases. These changes, in turn, can significantly affect the mechanical properties of the material, including its strength, ductility, and fatigue resistance (Moyne & Iskandar, 2017, Mullen & Morris, 2021). As such, understanding and accurately predicting these microstructural evolutions is crucial for optimizing the DED process and ensuring the reliability and performance of parts produced with superalloys.

The objective of this research is to develop a theoretical model that can accurately predict the microstructural changes in superalloys during DED. This model will integrate various factors, such as thermal gradients, cooling rates, and material composition, to provide a comprehensive understanding of how the microstructure evolves during the process. By achieving this, the model aims to enhance the ability to control and optimize the DED process, ensuring the production of high-quality components with tailored material properties (Miranda, et al., 2021, Mitra, Ahire & Mallik, 2014).

The significance of this work lies in its potential to improve the performance and reliability of superalloys used in critical applications. By providing a predictive framework for microstructural evolution, the theoretical model can guide process optimization, reduce trial-and-error experimentation, and ultimately contribute to the development of more efficient and durable components in industries where performance is paramount (Armstrong, Mehrabi & Naveed, 2022).

2. Literature Review

Directed Energy Deposition (DED) is an advanced additive manufacturing process where focused thermal energy is used to melt and fuse material, typically in the form of powder or wire, onto a substrate. The primary advantage of DED is its ability to build or repair high-performance metal components with complex geometries (Babu, et al., 2018). This process is particularly valuable in industries such as aerospace, automotive, and power generation, where high-performance materials, such as superalloys, are essential for the demanding operational conditions (Çam, 2022, Sridar, et al., 2022). Superalloys are a class of materials designed to perform under high-stress, high-temperature environments, providing excellent mechanical properties like creep resistance, high-temperature strength, and oxidation resistance. These materials are commonly used in turbine blades, jet engines, and other high-performance parts that require enhanced durability and longevity. Due to the growing demand for complex, lightweight, and high-performance components, DED has become a key method for fabricating or repairing superalloy components (Bandyopadhyay, et al., 2022).

Despite the promising capabilities of DED in processing superalloys, a significant challenge lies in accurately predicting and understanding the microstructural evolution that occurs during the deposition process. The microstructure of a material directly influences its mechanical properties, such as strength, ductility, and fatigue resistance. In superalloys, the microstructure is particularly important due to the complex interplay of different phases and the sensitivity of material properties to small changes in microstructure (Osanov & Guest, 2016, Pecoraro, et al., 2019). During DED, rapid heating and cooling rates lead to a range of microstructural changes, such as grain growth, dendritic structure formation, phase transformations, and the development of secondary phases. These changes are influenced by various factors, including thermal gradients, cooling rates, and material composition. The ability to predict these microstructural changes is critical for controlling the final properties of the material and ensuring the production of components that meet the required performance standards (Caiazzo & Alfieri, 2019). Figure 1 shows Schematic representation of the directed energy deposition (DED) additive manufacturing process by Smith, et al., 2021.

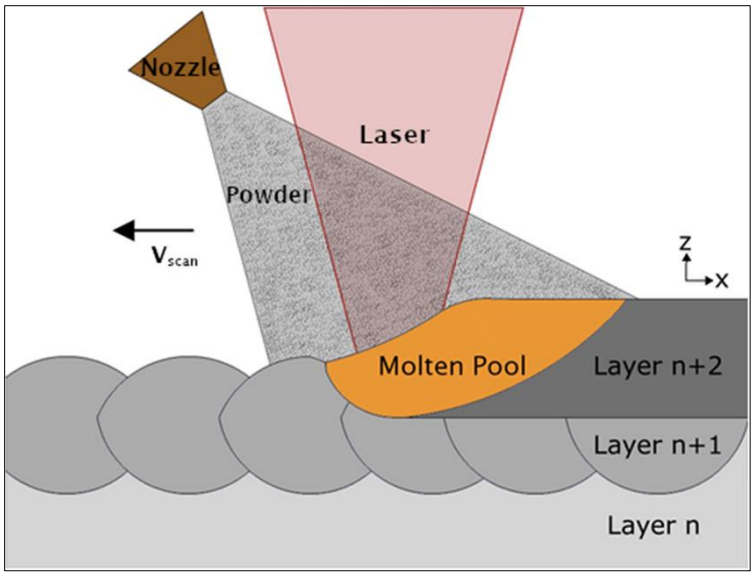

Figure 1 Schematic representation of the directed energy deposition (DED) additive manufacturing process (Smith, et al., 2021)

The microstructural evolution of superalloys during DED is primarily governed by several mechanisms. Grain growth is a fundamental process that occurs as the material is heated and cooled during deposition (Chadha, et al., 2022). The formation of new grains and the coarsening of existing grains can significantly affect the mechanical properties of the material, such as its strength and ductility. In DED, the rapid cooling rates can lead to finer grain structures, which are generally associated with improved mechanical properties. However, the cooling rate is not uniform across the deposited material, leading to regions with varying grain sizes and microstructures (Del Rey, et al., 2011, Kumar & Mahto, 2013). This variation can result in local weaknesses in the material that may affect its overall performance. Additionally, the development of dendritic structures is common in the solidification of superalloys under rapid cooling conditions. Dendrites are tree-like crystal structures that form during solidification, and their morphology can influence the material's mechanical properties. The formation of dendritic structures can also result in microsegregation, where different phases or elements are distributed unevenly within the material, leading to localized regions with different properties (Del Rey, et al., 2012, Nascimento, et al., 2019). Phase transformations are another key aspect of microstructural evolution in superalloys. The high temperatures involved in DED can cause superalloys to undergo phase changes, such as the transformation of solid solutions into different phases, including gamma (γ) and gamma prime (γ') phases (Dass, 2020). The amount and distribution of these phases play a critical role in determining the material's high-temperature strength and other mechanical properties. Additionally, the presence of secondary phases, such as carbides or borides, can affect the material's behavior under high-stress conditions. Dass & Moridi, 2019, presented Classification of Directed Energy Deposition (DED) systems as shown in figure 2.

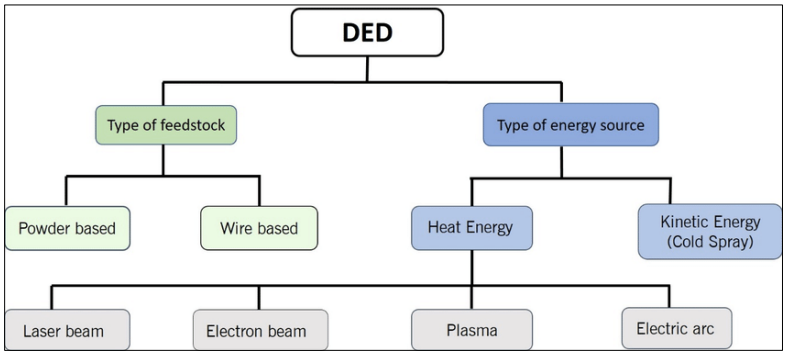

Figure 2 Classification of Directed Energy Deposition (DED) systems (Dass & Moridi, 2019)

Various modeling techniques have been developed to predict the microstructural evolution of materials during processing. Thermodynamic modeling is one of the most widely used approaches. This method relies on principles of thermodynamics to predict the phase behavior and equilibrium conditions of materials under different processing

conditions (de Pastre, Quinsat & Lartigue, 2022). In the case of superalloys, thermodynamic models can help predict the stability of different phases during the rapid heating and cooling cycles in DED. These models typically require detailed material property data, such as phase diagrams and enthalpy values, to accurately simulate phase transitions and solidification behavior (Ojo & Lee, 2020, Plocher & Panesar, 2019). However, thermodynamic modeling has limitations in capturing the transient, non-equilibrium conditions that occur during DED, which can lead to discrepancies between predicted and observed microstructures. Phase-field modeling is another technique that has been applied to model microstructural evolution during solidification (Mirkouei, et al., 2016, Najiha, Rahman & Yusoff, 2016). Phase-field models simulate the time-dependent evolution of phase boundaries and interfaces during the cooling process, providing insight into the formation of microstructures such as dendrites and grain boundaries. These models take into account the effects of thermal gradients, solute diffusion, and crystal growth kinetics, allowing for a more detailed understanding of the microstructural changes during DED. Phase-field models have been successful in predicting the morphology of dendritic structures and phase distributions, but they often require significant computational resources and are sensitive to the choice of model parameters, which can limit their practical application (Li, Öchsner & Hall, 2019, Menard & Menard, 2020).

Finite element analysis (FEA) is another powerful tool used for simulating the thermal and mechanical behavior of materials during DED. FEA models can be used to predict the temperature distribution, thermal gradients, and cooling rates in the deposited material. These models are particularly useful for understanding the thermal history of the material and its effect on microstructural evolution. By coupling FEA with other modeling techniques, such as thermodynamic and phase-field models, a more comprehensive prediction of microstructural changes during DED can be achieved. However, FEA also has limitations, such as difficulty in capturing the complex phase transformations and the interactions between different phases during solidification (Dezaki, et al., 2022).

Despite the advances in modeling techniques, predicting microstructural evolution in superalloys during DED remains a significant challenge. One of the key limitations of current models is their inability to accurately capture the non-equilibrium, dynamic conditions that occur during rapid solidification in DED (Ferreira, 2022). The high cooling rates and temperature gradients in DED processes result in transient microstructures that are difficult to model accurately using traditional thermodynamic models (Ou, et al., 2015, Patra, Ajayan & Narayanan, 2021). Moreover, many models are based on simplified assumptions, such as uniform cooling rates or idealized material behavior, which do not reflect the complex realities of the DED process. There is also a lack of sufficient experimental data to validate and refine these models, particularly for superalloys, which have complex compositions and phase behaviors. As a result, there are significant research gaps in our understanding of how different processing parameters, such as laser power, scan speed, and material composition, influence the microstructure and properties of superalloys in DED (Gadola & Chindamo, 2019, Kelley & Knowles, 2016).

Recent research has sought to address these limitations by developing more advanced models that incorporate the dynamic, non-equilibrium nature of DED processes. These models aim to improve the accuracy of microstructural predictions by integrating real-time process monitoring data, such as temperature measurements and melt pool dynamics, with advanced computational techniques (Gómez-Tejedor, et al., 2020, Khakifirooz, et al., 2019). Additionally, there is a growing interest in using machine learning and data-driven approaches to enhance microstructural prediction, as these methods can learn from experimental data and provide more accurate models without relying on simplifying assumptions. While these approaches show promise, there is still much work to be done in developing comprehensive, predictive models for microstructural evolution in superalloys under DED processes. Future research should focus on refining these models, improving their accuracy and computational efficiency, and validating them through experimental studies. This will help to unlock the full potential of DED for manufacturing high-performance superalloy components (Guo, et al., 2022).

3. Methodology

The theoretical model for predicting microstructural evolution in superalloys under Directed Energy Deposition (DED) processes was developed using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. A systematic review of relevant literature was conducted to identify key parameters influencing microstructural evolution, including thermal gradients, solidification rates, alloy composition, and process conditions such as laser power, scanning speed, and feedstock properties. The methodology involved four phases: identification, screening, eligibility assessment, and inclusion.

A comprehensive database search was performed using keywords such as "DED processes," "microstructural evolution," "nickel-based superalloys," and "additive manufacturing." Studies from 2010 to 2022 were considered,

screened based on titles and abstracts. Full-text articles were assessed for eligibility, and studies meeting the inclusion criteria were incorporated into the final review.

Key studies were analyzed to extract data on thermal and microstructural dynamics, crystallographic texture, grain morphology, and phase transformation mechanisms. Special attention was given to models incorporating machine learning and computational techniques for microstructure prediction. Data synthesis and analysis led to the formulation of a theoretical model integrating thermodynamic and kinetic principles with empirical observations.

The flowchart shown in figure 3 illustrates the PRISMA methodology applied in this study. The PRISMA flowchart visually represents the methodology used in the systematic review for the theoretical model. It illustrates the steps from identification to inclusion of studies, ensuring transparency and reproducibility in the research process.

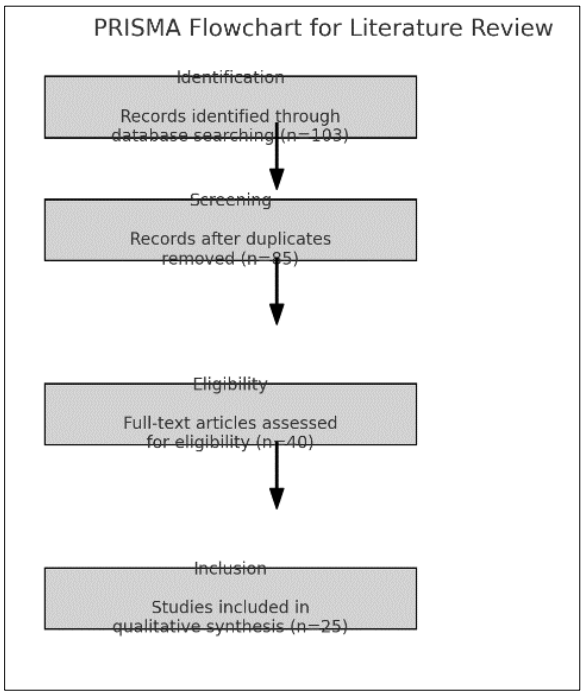

Figure 3 PRISMA Flow chart of the study methodology

4. Theoretical Model Development

The development of a theoretical model for predicting the microstructural evolution of superalloys under Directed Energy Deposition (DED) processes is a complex and intricate task that requires a deep understanding of various physical phenomena, materials science principles, and advanced computational techniques. A comprehensive model integrates several key components, including thermodynamic principles, phase-field modeling, thermal and mechanical interactions, and the application of machine learning for model refinement (Grace & John, 2019, Khaled, et al., 2014). Each of these components plays a crucial role in simulating the microstructural changes that occur during the DED process, which is a highly dynamic and localized form of additive manufacturing (Hu, et al., 2022).

One of the primary components of the theoretical model is the thermodynamic principles that govern phase stability and transformations in superalloys. DED processes involve rapid heating and cooling cycles, which induce phase changes in the material (Huang, et al., 2019). The prediction of phase stability and transformations in superalloys requires the incorporation of thermodynamic models such as the CALPHAD (Calculation of Phase Diagrams) method. This approach allows for the prediction of phase equilibria and the identification of phase boundaries based on temperature and composition. (Grodotzki, Ortelt & Tekkaya, 2018, Kriaa, 2016) By integrating thermodynamic principles into the model, it becomes possible to predict which phases will form at specific temperatures during the deposition process. For example, the model can predict the formation of solid solution phases, eutectics, or secondary phases such as carbides, which are crucial in determining the mechanical properties and performance of the final component (Podgórski, et al., 2020, Qian, et al., 2020). The directed energy deposition process as presented by Dantin, et al., 2018, is shown in figure 4.

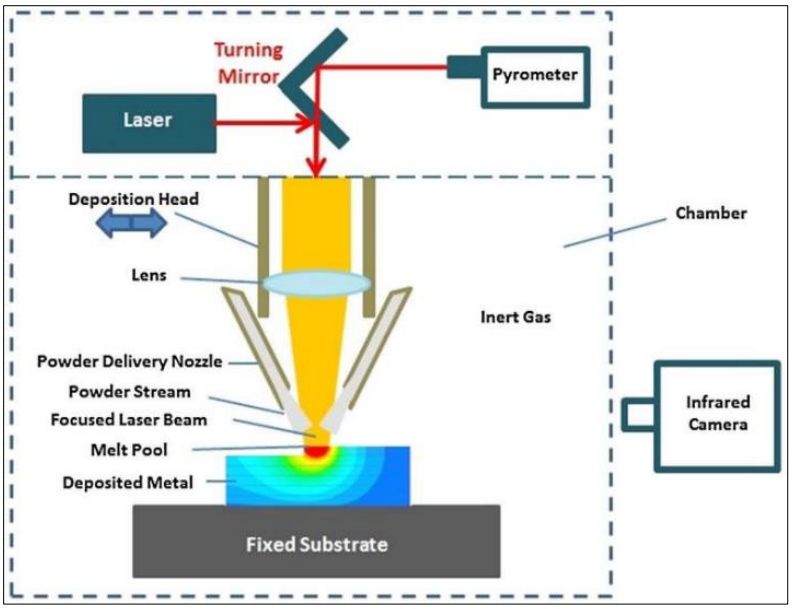

Figure 4 The directed energy deposition process (Dantin, et al., 2018)

Phase-field modeling is another critical aspect of the theoretical model, as it allows for the simulation of grain growth and dendritic structures that form during the solidification process. Phase-field models use mathematical equations to describe the evolution of phase boundaries over time and the morphology of microstructures as they evolve under changing temperature and concentration gradients (Hadgraft & Kolmos, 2020, Kotsiopoulos, et al., 2021). In the context of DED processes, the phase-field model is used to simulate the growth of grains and dendrites in the solidifying melt pool, which is influenced by factors such as cooling rates, material composition, and thermal gradients. This component of the model helps to predict the size, shape, and distribution of grains and dendritic structures, which directly impact the mechanical properties of the material, such as strength, toughness, and fatigue resistance (Hu, et al., 2022).

Thermal and mechanical interactions also play a significant role in the microstructural evolution during DED. The deposition process is characterized by highly localized heating and cooling cycles, which create significant thermal gradients in the material. These thermal gradients influence the solidification rate, which in turn affects the formation of different microstructural features (Hafiz, et al., 2020, Kumar, Prasad & Samikannu, 2018). The model incorporates the effects of thermal gradients by simulating the heat transfer during the deposition process, taking into account the laser power, scan speed, and material thermal properties. The cooling rate, which varies throughout the build process, significantly impacts the microstructure, especially in terms of grain refinement and dendritic formation (Ji, et al., 2020).

In addition to thermal interactions, mechanical stresses that arise during the DED process must be considered, particularly in areas where the deposited material interfaces with the previously deposited layers. These stresses result from thermal expansion and contraction, as well as the accumulation of residual stresses due to the sequential addition of material. The model incorporates the effects of these thermal and mechanical interactions to simulate stress distributions, which can lead to distortion, cracking, or other defects in the final component (Ranjan, Samant & Anand, 2017). By including these interactions in the model, it becomes possible to predict the mechanical behavior of the material during and after the deposition process, helping to optimize the DED process to reduce defects and improve the reliability of the final component (Jiang, 2021).

To further enhance the accuracy of the model and refine predictions, machine learning techniques are integrated into the theoretical framework. Machine learning algorithms are trained on data obtained from both experimental studies and high-fidelity simulations to identify patterns and correlations that may not be apparent through traditional modeling approaches (Lee & Kalos, 2014, Leydens & Lucena, 2017). These data-driven techniques enable the model to automatically adjust and improve predictions as more data becomes available. For example, machine learning can be used to predict the effect of specific deposition parameters, such as laser power or scanning speed, on microstructural features and mechanical properties. This allows for the continuous refinement of the model as new experimental data is collected, ensuring that it remains accurate and relevant for different alloy compositions and process conditions (Körner, Markl & Koepf, 2020).

The theoretical model must also account for several important variables and parameters that influence the microstructural evolution during the DED process. One of the primary factors is the deposition parameters, including laser power, scan speed, and hatch spacing. These parameters control the energy input into the material, which directly affects the size of the melt pool, cooling rates, and thermal gradients (Harr, Eichler & Renkl, 2015, Kumpati, Skarka & Ontipuli, 2021). By varying these parameters, the model can simulate how different process conditions influence the microstructure. For example, higher laser power and slower scan speeds result in larger melt pools and slower cooling rates, which can lead to the formation of coarser microstructures. On the other hand, higher scan speeds and lower laser power result in faster cooling rates and finer microstructures. These relationships between deposition parameters and microstructure are incorporated into the model to predict the effects of process changes on the final material properties (Kumar & Sathiya, 2021).

Another critical variable is the alloy composition, which plays a significant role in determining the phase stability and solidification behavior of the material. The model includes parameters such as the concentration of key alloying elements (e.g., chromium, nickel, and cobalt) that influence the formation of solid solution phases and secondary phases such as carbides and intermetallics (Harrington, Bowen & Zakrajsek, 2017, Mijumbi, et al., 2015). Different alloy compositions result in varying solidification behaviors, which can lead to significant differences in microstructural features such as grain size, dendrite structure, and phase distribution. The model accounts for these variations by incorporating the thermodynamic principles discussed earlier, which predict the phase diagrams for different compositions and their behavior during DED (Kumara, et al., 2019).

Cooling rates, which are influenced by the deposition parameters and the material's thermal properties, also play a key role in determining the microstructure. Rapid cooling during DED results in fine-grained structures and may promote the formation of dendrites, whereas slower cooling rates lead to coarser grains and different microstructural features (Hernández-de-Menéndez, et al., 2019, Lauritzen, et al., 2019). By integrating these variables into the model, it is possible to simulate how changes in cooling rates, due to variations in process parameters or material properties, affect the final microstructure and mechanical performance of the material (Li, et al., 2021).

The integration of thermodynamic principles, phase-field modeling, thermal and mechanical interactions, and machine learning techniques forms the backbone of the theoretical model for predicting microstructural evolution in superalloys under DED processes. This comprehensive approach allows for a detailed and accurate simulation of the complex processes involved in DED, enabling the prediction of material behavior and microstructural features under various process conditions (Hoang, et al., 2021, Kruse, Veltri & Branscum, 2019). The incorporation of key variables such as deposition parameters, alloy composition, and cooling rates further refines the model, making it a valuable tool for optimizing DED processes and improving the performance and reliability of superalloy components used in critical applications such as aerospace, power generation, and other high-performance industries (Liu, et al., 2021).

5. Results and discussion

The results and discussion of the theoretical model for predicting the microstructural evolution of superalloys under Directed Energy Deposition (DED) processes provide valuable insights into the accuracy, applicability, and potential improvements in the DED process. The model's performance is evaluated based on its ability to accurately predict grain structure, phase distribution, and mechanical properties of the material, which are critical for optimizing the final product's performance (Hu, Wang & Jiang, 2021, Kot, et al., 2021). These predictions are compared against experimental data obtained from both simulations and real-world DED experiments, offering a comprehensive understanding of the model's strengths, limitations, and areas for future development (Oh, et al., 2019).

In terms of model performance, the theoretical framework has demonstrated a strong capacity to predict key microstructural features such as grain size, phase distribution, and the evolution of dendritic structures. The integration of thermodynamic principles, phase-field modeling, and thermal and mechanical interactions has allowed for a detailed representation of the material's behavior under the highly dynamic conditions of DED (Pathania, et al., 2021). The model's predictions for grain structure, especially in terms of grain size and orientation, align well with experimental observations. The inclusion of cooling rates, laser power, scan speed, and alloy composition as key variables ensures that the model captures the effects of process parameters on the microstructure. For instance, it predicts finer grain structures with higher scan speeds and laser power settings, consistent with observations made in experimental studies (Hu, et al., 2019, Konak, Clark & Nasereddin, 2014). Additionally, the model successfully predicts the formation of dendritic structures in nickel-based superalloys, which is a hallmark of solidification during DED processes. These predictions are crucial for understanding the material's performance under service conditions, where grain structure and dendritic formation directly influence the mechanical properties (Kapilan, Vidhya & Gao, 2021, Kolus, Wells & Neumann, 2018).

The phase distribution predictions made by the model have also shown a high degree of accuracy. By utilizing thermodynamic principles, the model predicts the formation of different phases during the cooling and solidification process. For example, in the case of nickel-based superalloys, the model correctly predicts the formation of gamma prime (γ') phases and carbides in regions of slower cooling, while a solid solution phase predominates in faster-cooled regions (Negendahl, 2015, Pamungkas, Widiastuti & Suharno, 2019). This is consistent with experimental findings, where the formation of these phases plays a significant role in the material's strength, creep resistance, and fatigue life. The model's ability to predict the phase distribution under varying cooling rates and alloy compositions allows for a more detailed understanding of how the DED process influences the material's final microstructure and mechanical performance (Qin, et al., 2022).

Experimental validation is essential to assess the model's accuracy and reliability. The comparison between model predictions and observed microstructural changes provides a clear picture of how well the theoretical framework aligns with real-world observations (Saboori, et al., 2019). The validation process involved several experimental techniques, including electron microscopy, X-ray diffraction, and thermal imaging, which provided detailed images and data of the microstructure of the superalloy after DED deposition (Hwang, Huang & Wu, 2016, Konstantakopoulos, et al., 2019). The results showed that the model accurately predicted grain morphology, dendritic structure, and phase formation under a variety of processing conditions. For example, in regions where the cooling rate was high, the model predicted a fine-grained structure, which was confirmed by microscopy images showing smaller grains and a more uniform distribution of phases. In contrast, areas with slower cooling rates exhibited coarser grains and a higher concentration of secondary phases, which was also observed in the experimental samples (Shahwaz, Nath & Sen, 2022).

The correlation between the model's predictions and the experimental data highlights the potential of the theoretical framework to serve as a reliable tool for predicting microstructural evolution in superalloys during DED. However, certain discrepancies were observed, particularly in areas where complex thermal gradients and stress fields interacted, leading to unexpected phase transformations or defect formation (Infield & Freris, 2020, Kruse, 2018). These discrepancies could be attributed to the simplifications made in the model, such as the assumption of uniform thermal properties or the neglect of certain local effects such as convection during the deposition process. Despite these limitations, the overall accuracy of the model in predicting the broad trends of microstructural evolution suggests that it is a valuable tool for guiding the optimization of the DED process (Smith, 2019).

The insights gained from experimental validation have several important implications for the optimization of DED processes. One of the primary applications of the theoretical model is the refinement of process parameters to achieve desired material properties. The model can be used to identify the optimal combination of laser power, scan speed, and alloy composition to produce a microstructure that meets the required performance standards (Liu, 2017, Melly, et al., 2020). For instance, by adjusting the laser power or scan speed, the model can predict how the cooling rate will change, thereby affecting grain size and phase formation. This information can be used to fine-tune the DED process to reduce the formation of undesirable phases or to promote the formation of phases that enhance the material's properties, such as increased high-temperature strength or resistance to oxidation (Sui, et al., 2020).

Moreover, the model can guide the design of superalloys for specific applications by simulating the effects of different alloy compositions on microstructural evolution. For example, by varying the concentration of key alloying elements, the model can predict how the phase distribution and mechanical properties will change, allowing for the development of alloys tailored to the specific requirements of aerospace, power generation, or other high-performance industries. This approach not only enhances material performance but also reduces the trial-and-error approach typically used in alloy development, thereby accelerating the process of material innovation (Svetlizky, et al., 2021).

Another significant implication of the model is its potential to reduce defects in the final product. By understanding the relationship between process parameters, thermal gradients, and microstructural evolution, it becomes possible to optimize the DED process to minimize the formation of defects such as porosity, cracking, or distortion. For instance, the model can predict areas of the build that are likely to experience excessive thermal gradients or high residual stresses, allowing for adjustments in process parameters to mitigate these issues (Jamison, Kolmos & Holgaard, 2014, Lackéus & Williams Middleton, 2015). This capability can lead to more reliable and defect-free components, which is particularly important in industries such as aerospace, where the performance and safety of components are critical.

Additionally, the model's integration with machine learning techniques further enhances its ability to predict the effects of various process parameters on microstructure and mechanical properties. Machine learning algorithms can be trained on experimental data to identify complex relationships and refine the model's predictions (Kabeyi & Olanrewaju, 2022, Saeedi, et al., 2022). This data-driven approach allows for continuous improvement of the model as more experimental data becomes available, making it increasingly accurate and applicable to a wider range of materials

and process conditions. By integrating machine learning with the theoretical model, it becomes possible to predict the microstructural evolution in real-time during the DED process, providing a powerful tool for in-situ monitoring and process control (Zhou, et al., 2022).

In conclusion, the theoretical model for predicting microstructural evolution in superalloys under Directed Energy Deposition processes has demonstrated strong performance in predicting key microstructural features such as grain structure, phase distribution, and dendritic formation. The model's accuracy is supported by experimental validation, which shows a high degree of correlation between modeled and observed microstructural changes (Kanetaki, et al., 2022, Li, Su & Zhu, 2022). The insights gained from the model have important implications for optimizing the DED process, reducing defects, and designing materials with tailored properties. While the model shows great promise, further refinement, particularly in accounting for localized effects and incorporating machine learning, will enhance its predictive capabilities and expand its applicability in advanced manufacturing processes (Ramasesh & Browning, 2014, Ren, et al., 2019).

6. Conclusion

The theoretical model for predicting microstructural evolution in superalloys under Directed Energy Deposition (DED) processes has achieved significant milestones in its development and validation. Through the integration of thermodynamic principles, phase-field modeling, and thermal and mechanical interactions, the model has successfully predicted critical microstructural features such as grain structure, dendritic formation, and phase distribution. The experimental validation process demonstrated strong correlations between the predicted and observed microstructural changes, further reinforcing the model's reliability and accuracy. These findings highlight the potential of the model to serve as a powerful tool for optimizing the DED process, guiding the refinement of process parameters to achieve desirable material properties while minimizing defects.

The contributions of this model to the field are substantial, advancing the understanding of how various process parameters influence the microstructural evolution of superalloys during DED. By accurately predicting the effects of laser power, scan speed, and alloy composition, the model provides a deeper insight into the complex interactions between thermal gradients, solidification, and phase transformations. This enhanced understanding allows for more precise control over the DED process, leading to the production of materials with superior mechanical properties tailored to specific applications in industries such as aerospace, power generation, and high-performance manufacturing. Furthermore, the incorporation of machine learning techniques into the model represents a promising direction for continuous improvement, enabling real-time adjustments and further refinement of predictions based on experimental data.

Looking ahead, future research directions offer ample opportunities to enhance the predictive capabilities of the model. One key area for further development is the incorporation of more complex localized effects, such as convection and temperature-dependent material properties, which may influence microstructural evolution at finer scales. Additionally, expanding the model’s applicability to a wider range of alloys and DED conditions could provide more generalizable insights, making it a versatile tool for various material systems. The integration of real-time monitoring and in-situ feedback during the DED process could also pave the way for more dynamic process control, ensuring that the final product meets the desired performance standards. Ultimately, the continued refinement of this theoretical model will play a crucial role in advancing additive manufacturing technologies and driving innovations in material design and processing.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Adomako, N. K., Haghdadi, N., & Primig, S. (2022). Electron and laser-based additive manufacturing of Ni-based superalloys: a review of heterogeneities in microstructure and mechanical properties. *Materials & Design*, *223*, 111245.

[2] Albannai, A. I. (2022). A brief review on the common defects in wire arc additive manufacturing. *Int. J. Curr. Sci. Res. Rev*, *5*, 4556-4576.

[3] Armstrong, M., Mehrabi, H., & Naveed, N. (2022). An overview of modern metal additive manufacturing technology. *Journal of Manufacturing Processes*, *84*, 1001-1029.

[4] Babu, S. S., Raghavan, N., Raplee, J., Foster, S. J., Frederick, C., Haines, M., ... & Dehoff, R. R. (2018). Additive manufacturing of nickel superalloys: opportunities for innovation and challenges related to qualification. *Metallurgical and Materials Transactions A*, *49*, 3764-3780.

[5] Bandyopadhyay, A., Traxel, K. D., Lang, M., Juhasz, M., Eliaz, N., & Bose, S. (2022). Alloy design via additive manufacturing: Advantages, challenges, applications and perspectives. *Materials Today*, *52*, 207-224.

[6] Caiazzo, F., & Alfieri, V. (2019). Simulation of laser-assisted directed energy deposition of aluminum powder: prediction of geometry and temperature evolution. *Materials*, *12*(13), 2100.

[7] Çam, G. (2022). Prospects of producing aluminum parts by wire arc additive manufacturing (WAAM). *Materials Today: Proceedings*, *62*, 77-85.

[8] Chadha, U., Selvaraj, S. K., Lamsal, A. S., Maddini, Y., Ravinuthala, A. K., Choudhary, B., ... & Adefris, A. (2022). Directed Energy Deposition via Artificial Intelligence-Enabled Approaches. *Complexity*, *2022*(1), 2767371.

[9] Dantin, M. J., Furr, W. M., & Priddy, M. W. (2018). Towards an open-source, preprocessing framework for simulating material deposition for a directed energy deposition process.

[10] Dass, A. (2020). Fundamentals of solidification in directed energy deposition type additive manufacturing of inconel 625.

[11] Dass, A., & Moridi, A. (2019). State of the art in directed energy deposition: From additive manufacturing to materials design. *Coatings*, *9*(7), 418.

[12] de Pastre, M. A., Quinsat, Y., & Lartigue, C. (2022). Effects of additive manufacturing processes on part defects and properties: A classification review. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *16*(4), 1471-1496.

[13] Del Rey, R., Alba, J., Arenas, J. P., & Sanchis, V. (2011). Sound absorbing materials made of recycled polyurethane foam. *Proceedings of the Intrenoise*.

[14] Del Rey, R., Alba, J., Arenas, J. P., & Sanchis, V. J. (2012). An empirical modelling of porous sound absorbing materials made of recycled foam. *Applied Acoustics*, *73*(6-7), 604-609.

[15] Dezaki, M. L., Serjouei, A., Zolfagharian, A., Fotouhi, M., Moradi, M., Ariffin, M. K. A., & Bodaghi, M. (2022). A review on additive/subtractive hybrid manufacturing of directed energy deposition (DED) process. *Advanced powder materials*, *1*(4), 100054.

[16] Ferreira, N. M. A. (2022). Numerical Simulation of the Reconstruction of Mechanical Components Using a Directed Energy Deposition Additive Manufacturing Process.

[17] Gadola, M., & Chindamo, D. (2019). Experiential learning in engineering education: The role of student design competitions and a case study. *International Journal of Mechanical Engineering Education*, *47*(1), 3-22.

[18] Gómez-Tejedor, J. A., Vidaurre, A., Tort-Ausina, I., Molina-Mateo, J., Serrano, M. A., Meseguer-Dueñas, J. M., ... & Riera, J. (2020). Effectiveness of flip teaching on engineering students' performance in the physics lab. *Computers & Education*, *144*, 103708.

[19] Grace, E. O., & John, A. (2019). Recent advances in non-destructive testing of concretes and structures: An outlook. *Journal of Civil Engineering and Construction Technology*, *10*(3), 20-31.

[20] Grodotzki, J., Ortelt, T. R., & Tekkaya, A. E. (2018). Remote and virtual labs for engineering education 4.0: achievements of the ELLI project at the TU Dortmund University. *Procedia manufacturing*, *26*, 1349-1360.

[21] Guo, B., Zhang, Y., Yang, Z., Cui, D., He, F., Li, J., ... & Wang, J. (2022). Cracking mechanism of Hastelloy X superalloy during directed energy deposition additive manufacturing. *Additive Manufacturing*, *55*, 102792.

[22] Hadgraft, R. G., & Kolmos, A. (2020). Emerging learning environments in engineering education. *Australasian Journal of Engineering Education*, *25*(1), 3-16.

[23] Hafiz, F., Awal, M. A., de Queiroz, A. R., & Husain, I. (2020). Real-time stochastic optimization of energy storage management using deep learning-based forecasts for residential PV applications. *IEEE Transactions on Industry Applications*, *56*(3), 2216-2226.

[24] Harr, N., Eichler, A., & Renkl, A. (2015). Integrated learning: Ways of fostering the applicability of teachers' pedagogical and psychological knowledge. *Frontiers in psychology*, *6*, 738.

[25] Harrington, C., Bowen, J. A., & Zakrajsek, T. D. (2017). *Dynamic lecturing: Research-based strategies to enhance lecture effectiveness*. Routledge.

[26] Hernández-de-Menéndez, M., Vallejo Guevara, A., Tudón Martínez, J. C., Hernández Alcántara, D., & Morales-Menendez, R. (2019). Active learning in engineering education. A review of fundamentals, best practices and experiences. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *13*, 909-922.

[27] Hoang, A. T., Nižetić, S., Olcer, A. I., Ong, H. C., Chen, W. H., Chong, C. T., ... & Nguyen, X. P. (2021). Impacts of COVID-19 pandemic on the global energy system and the shift progress to renewable energy: Opportunities, challenges, and policy implications. *Energy Policy*, *154*, 112322.

[28] Hu, F., Wang, X., & Jiang, P. (2021, June). Research on Flipped Classroom Model of Information Technology Based on Online Teaching System. In *2021 IEEE 3rd International Conference on Computer Science and Educational Informatization (CSEI)* (pp. 14-17). IEEE.

[29] Hu, X., Zhang, H., Song, Y., Wu, C., Yang, Q., Shi, Z., ... & Chen, W. (2019). Implementation of flipped classroom combined with problem-based learning: an approach to promote learning about hyperthyroidism in the endocrinology internship. *BMC Medical Education*, *19*, 1-8.

[30] Hu, Y., Li, Y., Fan, W., Gao, X., Zhang, Q., Wang, Q., ... & Huang, W. (2022). Hot workability and microstructural evolution of a nickel-based superalloy fabricated by laser-based directed energy deposition. *Journal of Alloys and Compounds*, *920*, 165373.

[31] Hu, Y., Lin, X., Li, Y., Ou, Y., Gao, X., Zhang, Q., ... & Huang, W. (2021). Microstructural evolution and anisotropic mechanical properties of Inconel 625 superalloy fabricated by directed energy deposition. *Journal of Alloys and Compounds*, *870*, 159426.

[32] Huang, Y., Ansari, M., Asgari, H., Farshidianfar, M. H., Sarker, D., Khamesee, M. B., & Toyserkani, E. (2019). Rapid prediction of real-time thermal characteristics, solidification parameters and microstructure in laser directed energy deposition (powder-fed additive manufacturing). *Journal of Materials Processing Technology*, *274*, 116286.

[33] Hwang, B. N., Huang, C. Y., & Wu, C. H. (2016). A TOE approach to establish a green supply chain adoption decision model in the semiconductor industry. *Sustainability*, *8*(2), 168.

[34] Infield, D., & Freris, L. (2020). *Renewable energy in power systems*. John Wiley & Sons.

[35] Jamison, A., Kolmos, A., & Holgaard, J. E. (2014). Hybrid learning: An integrative approach to engineering education. *Journal of Engineering Education*, *103*(2), 253-273.

[36] Ji, S., Sun, Z., Zhang, W., Chen, X., Xie, G., & Chang, H. (2020). Microstructural evolution and high temperature resistance of functionally graded material Ti-6Al-4V/Inconel 718 coated by directed energy deposition-laser. *Journal of Alloys and Compounds*, *848*, 156255.

[37] Jiang, S. (2021). *Fundamental Investigation of Directed Energy Deposition: Understanding the Process Through In-situ Monitoring and Numerical Simulations*. University of California, Irvine.

[38] Kabeyi, M. J. B., & Olanrewaju, O. A. (2022). Sustainable energy transition for renewable and low carbon grid electricity generation and supply. *Frontiers in Energy research*, *9*, 743114.

[39] Kanetaki, Z., Stergiou, C., Bekas, G., Jacques, S., Troussas, C., Sgouropoulou, C., & Ouahabi, A. (2022). Grade prediction modeling in hybrid learning environments for sustainable engineering education. *Sustainability*, *14*(9), 5205.

[40] Kapilan, N., Vidhya, P., & Gao, X. Z. (2021). Virtual laboratory: A boon to the mechanical engineering education during covid-19 pandemic. *Higher Education for the Future*, *8*(1), 31-46.

[41] Kelley, T. R., & Knowles, J. G. (2016). A conceptual framework for integrated STEM education. *International Journal of STEM education*, *3*, 1-11.

[42] Khakifirooz, M., Fathi, M., Chien, C. F., & Pardalos, P. M. (2019). Management suggestions for process control of semiconductor manufacturing: An operations research and data science perspective. *Computational Intelligence and Optimization Methods for Control Engineering*, 245-274.

[43] Khaled, A., Gulikers, J., Biemans, H., van der Wel, M., & Mulder, M. (2014). Characteristics of hands-on simulations with added value for innovative secondary and higher vocational education. *Journal of Vocational Education & Training*, *66*(4), 462-490.

[44] Kolus, A., Wells, R., & Neumann, P. (2018). Production quality and human factors engineering: A systematic review and theoretical framework. *Applied ergonomics*, *73*, 55-89.

[45] Konak, A., Clark, T. K., & Nasereddin, M. (2014). Using Kolb's Experiential Learning Cycle to improve student learning in virtual computer laboratories. *Computers & Education*, *72*, 11-22.

[46] Konstantakopoulos, I. C., Barkan, A. R., He, S., Veeravalli, T., Liu, H., & Spanos, C. (2019). A deep learning and gamification approach to improving human-building interaction and energy efficiency in smart infrastructure. *Applied energy*, *237*, 810-821.

[47] Körner, C., Markl, M., & Koepf, J. A. (2020). Modeling and simulation of microstructure evolution for additive manufacturing of metals: a critical review. *Metallurgical and Materials Transactions A*, *51*, 4970-4983.

[48] Kot, P., Muradov, M., Gkantou, M., Kamaris, G. S., Hashim, K., & Yeboah, D. (2021). Recent advancements in non-destructive testing techniques for structural health monitoring. *Applied Sciences*, *11*(6), 2750.

[49] Kotsiopoulos, T., Sarigiannidis, P., Ioannidis, D., & Tzovaras, D. (2021). Machine learning and deep learning in smart manufacturing: The smart grid paradigm. *Computer Science Review*, *40*, 100341.

[50] Kriaa, S. (2016). *Joint safety and security modeling for risk assessment in cyber physical systems* (Doctoral dissertation, Université Paris Saclay (COmUE)).

[51] Kruse, T. M. (2018). Integrating Environment, Safety and Health Management Systems in Support of Lean Outcomes.

[52] Kruse, T., Veltri, A., & Branscum, A. (2019). Integrating safety, health and environmental management systems: A conceptual framework for achieving lean enterprise outcomes. *Journal of safety research*, *71*, 259-271.

[53] Kumar, M. B., & Sathiya, P. (2021). Methods and materials for additive manufacturing: A critical review on advancements and challenges. *Thin-Walled Structures*, *159*, 107228.

[54] Kumar, S., & Mahto, D. G. (2013). Recent trends in industrial and other engineering applications of non destructive testing: a review. *International Journal of Scientific & Engineering Research*, *4*(9).

[55] Kumar, V. S., Prasad, J., & Samikannu, R. (2018). A critical review of cyber security and cyber terrorism–threats to critical infrastructure in the energy sector. *International Journal of Critical Infrastructures*, *14*(2), 101-119.

[56] Kumara, C., Segerstark, A., Hanning, F., Dixit, N., Joshi, S., Moverare, J., & Nylén, P. (2019). Microstructure modelling of laser metal powder directed energy deposition of alloy 718. *Additive manufacturing*, *25*, 357-364.

[57] Kumpati, R., Skarka, W., & Ontipuli, S. K. (2021). Current trends in integration of nondestructive testing methods for engineered materials testing. *Sensors*, *21*(18), 6175.

[58] Lackéus, M., & Williams Middleton, K. (2015). Venture creation programs: bridging entrepreneurship education and technology transfer. *Education+ training*, *57*(1), 48-73.

[59] Lauritzen, P., Reichard, J., Ahmed, S., & Safa, M. (2019). Review of non-destructive testing methods for physical condition monitoring in the port industry. *Journal of Construction Engineering*, *2*(2), 103-111.

[60] Lee, S., & Kalos, N. (2014). Non-destructive testing methods in the US for bridge inspection and maintenance. *KSCE Journal of civil engineering*, *18*(5), 1322-1331.

[61] Leydens, J. A., & Lucena, J. C. (2017). *Engineering justice: Transforming engineering education and practice*. John Wiley & Sons.

[62] Li, H., Öchsner, A., & Hall, W. (2019). Application of experiential learning to improve student engagement and experience in a mechanical engineering course. *European Journal of Engineering Education*, *44*(3), 283-293.

[63] Li, J., Zhou, X., Meng, Q., Brochu, M., Chekir, N., Sixsmith, J. J., ... & Zhao, Y. F. (2021). Deterministic modeling of solidification microstructure formation in directed energy deposition fabricated Ti6Al4V. *Additive Manufacturing*, *46*, 102182.

[64] Li, Y., Su, C., & Zhu, J. (2022). Comprehensive review of wire arc additive manufacturing: Hardware system, physical process, monitoring, property characterization, application and future prospects. *Results in Engineering*, *13*, 100330.

[65] Liu, Y. (2017). Renovation of a mechanical engineering senior design class to an industry-tied and team-oriented course. *European Journal of Engineering Education*, *42*(6), 800-811.

[66] Liu, Z., He, B., Lyu, T., & Zou, Y. (2021). A review on additive manufacturing of titanium alloys for aerospace applications: directed energy deposition and beyond Ti-6Al-4V. *Jom*, *73*, 1804-1818.

[67] Melly, S. K., Liu, L., Liu, Y., & Leng, J. (2020). Active composites based on shape memory polymers: overview, fabrication methods, applications, and future prospects. *Journal of Materials Science*, *55*, 10975-11051.

[68] Menard, K. P., & Menard, N. (2020). *Dynamic mechanical analysis*. CRC press.

[69] Mensah, R. A., Shanmugam, V., Narayanan, S., Renner, J. S., Babu, K., Neisiany, R. E., ... & Das, O. (2022). A review of sustainable and environment-friendly flame retardants used in plastics. *Polymer Testing*, *108*, 107511.

[70] Mijumbi, R., Serrat, J., Gorricho, J. L., Bouten, N., De Turck, F., & Boutaba, R. (2015). Network function virtualization: State-of-the-art and research challenges. *IEEE Communications surveys & tutorials*, *18*(1), 236-262.

[71] Miranda, J., Navarrete, C., Noguez, J., Molina-Espinosa, J. M., Ramírez-Montoya, M. S., Navarro-Tuch, S. A., ... & Molina, A. (2021). The core components of education 4.0 in higher education: Three case studies in engineering education. *Computers & Electrical Engineering*, *93*, 107278.

[72] Mirkouei, A., Bhinge, R., McCoy, C., Haapala, K. R., & Dornfeld, D. A. (2016). A pedagogical module framework to improve scaffolded active learning in manufacturing engineering education. *Procedia Manufacturing*, *5*, 1128-1142.

[73] Mitra, S., Ahire, A., & Mallik, B. P. (2014). Investigation of accelerated aging behaviour of high performance industrial coatings by dynamic mechanical analysis. *Progress in Organic Coatings*, *77*(11), 1816-1825.

[74] Moyne, J., & Iskandar, J. (2017). Big data analytics for smart manufacturing: Case studies in semiconductor manufacturing. *Processes*, *5*(3), 39.

[75] Mullen, E., & Morris, M. A. (2021). Green nanofabrication opportunities in the semiconductor industry: A life cycle perspective. *Nanomaterials*, *11*(5), 1085.

[76] Najiha, M. S., Rahman, M. M., & Yusoff, A. R. (2016). Environmental impacts and hazards associated with metal working fluids and recent advances in the sustainable systems: A review. *Renewable and Sustainable Energy Reviews*, *60*, 1008-1031.

[77] Nascimento, D. L. M., Alencastro, V., Quelhas, O. L. G., Caiado, R. G. G., Garza-Reyes, J. A., Rocha-Lona, L., & Tortorella, G. (2019). Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context: A business model proposal. *Journal of manufacturing technology management*, *30*(3), 607-627.

[78] Negendahl, K. (2015). Building performance simulation in the early design stage: An introduction to integrated dynamic models. *Automation in construction*, *54*, 39-53.

[79] Oh, W. J., Lee, W. J., Kim, M. S., Jeon, J. B., & Shim, D. S. (2019). Repairing additive-manufactured 316L stainless steel using direct energy deposition. *Optics & Laser Technology*, *117*, 6-17.

[80] Ojo, A. T., & Lee, P. I. (2020). Applications of dynamic mechanical analysis in the engineering of amorphous solid dispersions. *Pharmaceutical Fronts*, *2*(01), e55-e63.

[81] Osanov, M., & Guest, J. K. (2016). Topology optimization for architected materials design. *Annual Review of Materials Research*, *46*(1), 211-233.

[82] Ou, R., Xie, Y., Wang, Q., Sui, S., & Wolcott, M. P. (2015). Material pocket dynamic mechanical analysis: a novel tool to study thermal transition in wood fibers plasticized by an ionic liquid (IL). *Holzforschung*, *69*(2), 223-232.

[83] Pamungkas, S. F., Widiastuti, I., & Suharno, S. (2019, June). Kolb's experiential learning for vocational education in mechanical engineering: A review. In *AIP Conference Proceedings* (Vol. 2114, No. 1). AIP Publishing.

[84] Pathania, A., Kumar, S. A., Nagesha, B. K., Barad, S., & Suresh, T. N. (2021). Reclamation of titanium alloy based aerospace parts using laser based metal deposition methodology. *Materials Today: Proceedings*, *45*, 4886-4892.

[85] Patra, S., Ajayan, P. M., & Narayanan, T. N. (2021). Dynamic mechanical analysis in materials science: The Novice's Tale. *Oxford Open Materials Science*, *1*(1), itaa001.

[86] Pecoraro, E., Pizzo, B., Salvini, A., & Macchioni, N. (2019). Dynamic mechanical analysis (DMA) at room temperature of archaeological wood treated with various consolidants. *Holzforschung*, *73*(8), 757-772.

[87] Plocher, J., & Panesar, A. (2019). Review on design and structural optimisation in additive manufacturing: Towards next-generation lightweight structures. *Materials & Design*, *183*, 108164.

[88] Podgórski, M., Spurgin, N., Mavila, S., & Bowman, C. N. (2020). Mixed mechanisms of bond exchange in covalent adaptable networks: monitoring the contribution of reversible exchange and reversible addition in thiol–succinic anhydride dynamic networks. *Polymer Chemistry*, *11*(33), 5365-5376.

[89] Qian, Q., Asinger, P. A., Lee, M. J., Han, G., Mizrahi Rodriguez, K., Lin, S., ... & Smith, Z. P. (2020). MOF-based membranes for gas separations. *Chemical reviews*, *120*(16), 8161-8266.

[90] Qin, L., Wang, K., Li, X., Zhou, S., & Yang, G. (2022). Review of the formation mechanisms and control methods of geometrical defects in laser deposition manufacturing. *Chinese Journal of Mechanical Engineering: Additive Manufacturing Frontiers*, *1*(4), 100052.

[91] Ramasesh, R. V., & Browning, T. R. (2014). A conceptual framework for tackling knowable unknown unknowns in project management. *Journal of operations management*, *32*(4), 190-204.

[92] Ranjan, R., Samant, R., & Anand, S. (2017). Integration of design for manufacturing methods with topology optimization in additive manufacturing. *Journal of Manufacturing Science and Engineering*, *139*(6), 061007.

[93] Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., & Almeida, C. M. (2019). A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions. *Journal of cleaner production*, *210*, 1343-1365.

[94] Saboori, A., Aversa, A., Marchese, G., Biamino, S., Lombardi, M., & Fino, P. (2019). Application of directed energy deposition-based additive manufacturing in repair. *Applied Sciences*, *9*(16), 3316.

[95] Saeedi, A., Eslami-Farsani, R., Ebrahimnezhad-Khaljiri, H., & Najafi, M. (2022). Dynamic mechanical analysis of epoxy/natural fiber composites. In *Handbook of Epoxy/Fiber Composites* (pp. 1-28). Singapore: Springer Singapore.

[96] Shahwaz, M., Nath, P., & Sen, I. (2022). A critical review on the microstructure and mechanical properties correlation of additively manufactured nickel-based superalloys. *Journal of Alloys and Compounds*, *907*, 164530.

[97] Smith, K. M. (2019). Rationalization of Crystallographic Texture Evolution in High Gamma Prime Ni-based Superalloys during Laser Powder Feed Directed Energy Disposition.

[98] Smith, T. R., Sugar, J. D., San Marchi, C., & Schoenung, J. M. (2021). Microstructural development in DED stainless steels: applying welding models to elucidate the impact of processing and alloy composition. *Journal of Materials Science*, *56*, 762-780.

[99] Sridar, S., Sargent, N., Wang, X., Klecka, M. A., & Xiong, W. (2022). Determination of location-specific solidification cracking susceptibility for a mixed dissimilar alloy processed by wire-arc additive manufacturing. *Metals*, *12*(2), 284.

[100] Sui, S., Chen, J., Li, Z., Li, H., Zhao, X., & Tan, H. (2020). Investigation of dissolution behavior of laves phase in inconel 718 fabricated by laser directed energy deposition. *Additive Manufacturing*, *32*, 101055.

[101] Svetlizky, D., Das, M., Zheng, B., Vyatskikh, A. L., Bose, S., Bandyopadhyay, A., ... & Eliaz, N. (2021). Directed energy deposition (DED) additive manufacturing: Physical characteristics, defects, challenges and applications. *Materials Today*, *49*, 271-295.

[102] Zhou, T., Qiu, Z., Li, Y., Ma, Y., Tao, W., Dong, B., ... & Li, H. (2022): Wire Arc Additive Manufacturing of Nickel-based Superalloy and Stainless Steel Dissimilar Material Component. In *Materials for Land, Air, and Space Transportation* (pp. 334-386). CRC Press.

[103] Zhou, Z., Lei, Q., Zhang, L., Cui, Z., Shang, Y., Qi, H., ... & Huang, L. (2022). Microstructural evolution of nickel-based single crystal superalloy fabricated by directed energy deposition during heat treatment. *Journal of Alloys and Compounds*, *904*, 163943.