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Numerical modeling and digital twins wire arc additive manufacturing

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Abstract: *Wire Arc Additive Manufacturing (WAAM) has become a valuable tool for cost-effective production of large metal structures with complex geometry using established arc-welding hardware and wire feedstock. However, the complexity of underlying physics makes it difficult to predict the geometry and stress state of final products. Heat accumulation, inter-pass temperature, and path planning influence bead shape and defect formation, while cyclic thermal loading induces residual stresses and distortion, which hinder repeatability and certification. High-fidelity numerical modelling, while being important for studying and optimization of WAAM process, remains unsuitable for real time simulation and control due to high computational cost. In order to overcome the limitations of pure physics-based models, the interest has shifted to hybrid workflows – combined physics-based and data-driven models calibrated by real-time sensing – embedded in Digital Twin architectures to support prediction, monitoring, and process control. The objective of this study is to systemise recent advances in multi-scale multi-physics numerical modelling for wire arc additive manufacturing (WAAM) and provide insight into Digital Twin (DT) architectures alongside data-driven approaches based on artificial intelligence (AI), machine learning (ML) and data management. The extensive literature review was performed to reveal advantages and limitations of these simulation method and how they could transition WAAM to intelligent manufacturing, driven by multiple data streams, with real-time monitoring, predictive analytics, and autonomous correction. The results of the review can be used in future studies to organize and assemble intelligent WAAM systems in laboratory experimental conditions with a perspective of industrial applications.*

Keywords: *Wire Arc Additive Manufacturing (WAAM), 3D-printing, FEM, CFD, digital twin, residual stress, distortion, defect prediction.*

Introduction

Additive manufacturing (AM), colloquially known as 3D-printing, has revolutionized various industrial sectors by enabling the efficient production of complex structures with tailored properties. This transformative technology encompasses a wide array of processes, systematically classified by the American Society for Testing and Materials (ASTM) [1] under seven primary categories, as illustrated in Fig. 1.

In particular, direct energy deposition (DED) processes involve melting material in the form of wire or powder using a laser, electric arc, or electron beam as a heat source and depositing the molten material layer by layer. These technologies are used in many industries, such as the aerospace industry, and can be used to create products from various materials, including metal alloys. For example, in 2023, Relativity Space, a private space company, successfully launched the world's first 3D-printed space rocket, demonstrating the high-impact capabilities of AM, specifically highlighting the application of Wire Arc Additive Manufacturing (WAAM) in creating large-scale, complex components.

Objective and research task

The objective of this research is to provide a systematic review of recent advances in numerical modelling for Wire Arc Additive Manufacturing (WAAM), focusing on Digital Twin (DT) frameworks and the use of Artificial Intelligence (AI) and Machine Learning (ML). It outlines the

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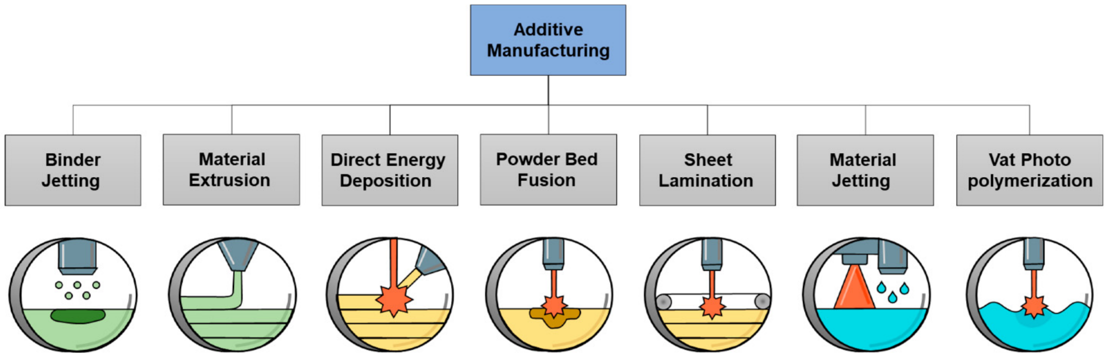


Fig. 1. Classification of additive manufacturing process. Reprinted from [2]

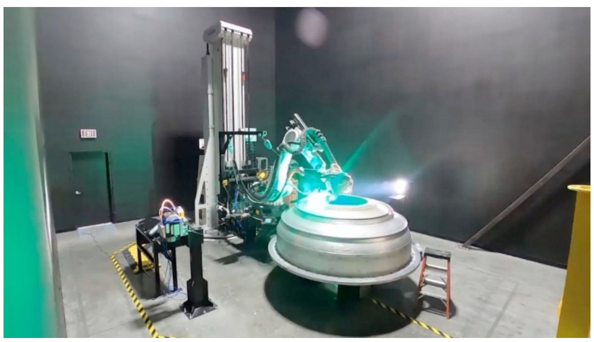


Fig. 2. The process of creating a part of a space rocket using Wire Arc Additive Manufacturing by Relativity Space

current state of WAAM, key challenges and the role of different modelling techniques in addressing them through optimization, property prediction, and defect detection

Methods

This research is conducted as a critical and topical review of recent advances in numerical modelling and Digital Twin (DT) applications in Wire Arc Additive Manufacturing (WAAM). The methods included the following steps:

Literature collection. Relevant scientific publications were retrieved from major academic databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and MDPI. The search covered the period from 2015 to 2025 to capture the most recent developments. The keywords used included: Wire Arc Additive Manufacturing (WAAM), numerical modelling, thermo-mechanical simulation, thermo-fluidic simulation, adaptive mesh refinement, finite element analysis (FEA), computational fluid dynamics (CFD), digital twin, artificial intelligence, and machine learning.

Selection criteria. Publications were included if they focused on numerical methods, process simulation, or integration of AI/ML with WAAM and Digital Twin frameworks. Studies limited to purely experimental work without modelling aspects were excluded. Priority was given to peer-reviewed journal articles, conference proceedings, and authoritative review papers.

Analysis approach. The selected works were categorized according to modelling scale (macro, meso, micro) and methodological focus (thermo-mechanical, thermo-fluidic, or hybrid approaches). Additional attention was paid to computational strategies such as adaptive mesh refinement and reduced-order surrogate modelling.

Special emphasis was placed on studies addressing the implementation of Digital Twin architectures in WAAM, with consideration of ISO 23247 reference models, service-oriented architectures, and the role of machine learning in defect detection, process monitoring, and predictive control.

Comparative synthesis. The findings were systematically compared to identify strengths, limitations, and future research opportunities in each category. Both qualitative synthesis (descriptive comparison) and quantitative data (e.g., deposition rates, error reduction, computational efficiency) were summarized.

By following these structured methods, the review ensures comprehensive coverage of the state-of-the-art, identifies technological trends, and outlines research directions for the development of WAAM simulations.

Overview of WAAM technology

WAAM has evolved from automated welding processes. It involves creating metallic components layer by layer using an electric arc as the heat source to melt a metal wire feedstock. The molten metal is systematically deposited to form three-dimensional structures.

WAAM processes are categorized based on the type of electric arc heat source used. The three main types are based on conventional welding methods: Gas Metal Arc Welding (GMAW), Gas Tungsten Arc Welding (GTAW) and Plasma Arc Welding (PAW).

Gas Metal Arc (GMAW)-based Wire Arc Additive Manufacturing (WAAM), also known as metal inert gas

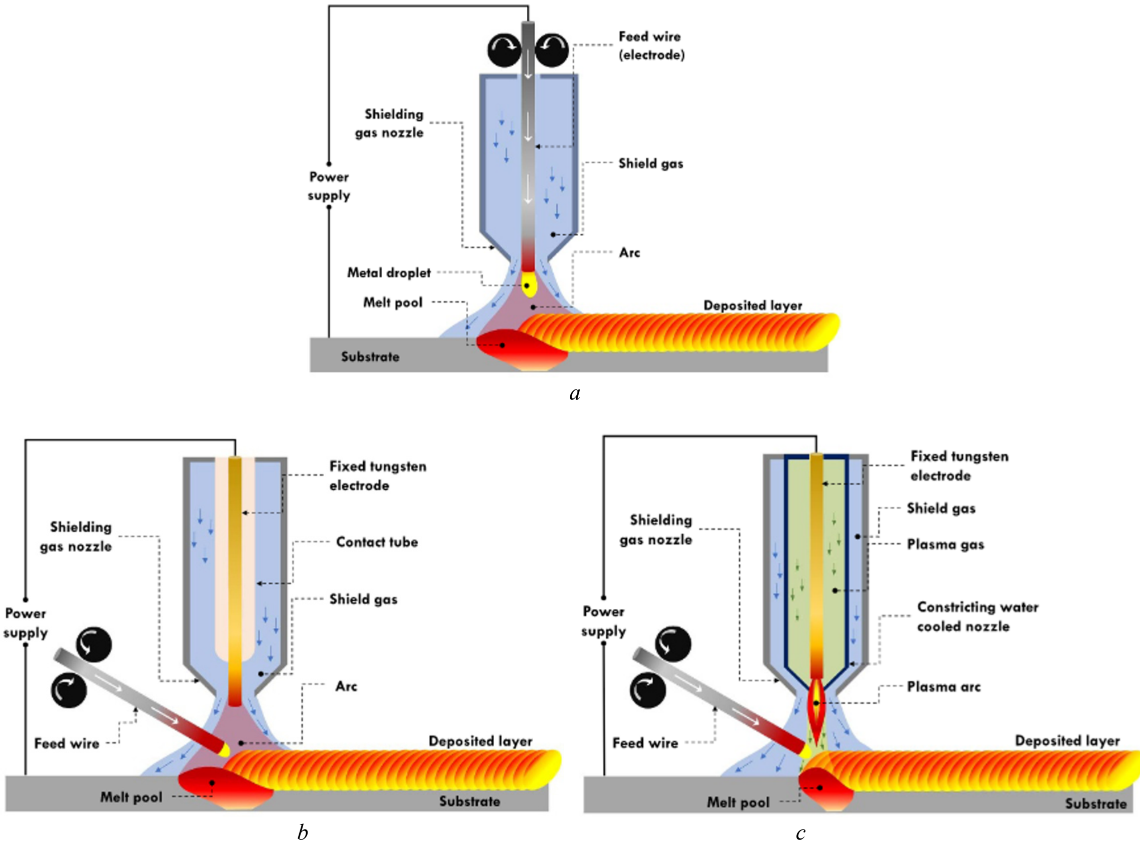


Fig. 3. Schematic of WAAM types: (*a*) GMAW, (*b*) GTAW and (*c*) PAW. Reprinted from [3]

(MIG) or metal active gas (MAG), is the most common WAAM technique due to its high productivity and suitability for automation. The process utilizes a consumable wire as both the electrode and feedstock, which is melted by an electric arc. A defining characteristic is the coupling of the wire feed rate with the arc current, which controls the melting rate. GMAW-based WAAM typically achieves higher deposition rates of 3–4 kg/h [3]. It is a versatile process compatible with a wide range of materials, including steel (e.g., ER70S-6) and aluminium alloys (e.g., 5356, 5556, and 4043). Several process variants exist to enhance performance. Cold Metal Transfer (CMT) is a modified short-circuit process that retracts the wire during the short circuit. This results in a low-heat input, which improves arc stability, minimizes spatter, and allows for precise energy distribution, thereby reducing thermal distortion [3], [4]. This control comes at the cost of a slightly lower deposition rate of 2–3 kg/h [3]. Other variations include Tandem GMAW, which employs two wires to increase the deposition rate up to 8 kg/h, and Double-electrode GMAW, which integrates a GTAW torch to lower the heat flux to the substrate [3].

Gas Tungsten Arc Welding (GTAW)-based WAAM uses a non-consumable tungsten electrode (usually the cathode) in an inert gas environment, while depositing material is fed separately [3], [5]. Thus, wire feed rate and the arc current can be controlled individually. The arc efficiency is slightly lower than those of GMAW. Orientation of feed wire can affect structure accuracy in GTAW-based processes [6]. Typical deposition rate is approximately 1–2 kg/h [3]

Plasma Arc Welding (PAW)-based WAAM uses a constricted arc plasma as the heat source [3], [5]. This results in a more focused heat flux, comparing to GTAW or GMAW and a smaller heat-affected zone, making this type of WAAM suitable for microscale applications [3]. Typical deposition rate is approximately 2–4 kg/h [3]

Hot-Wire Arc Additive Manufacturing (HWAAM) is an another process variant involving a secondary power source connected to the filler wire, which assists in melting the material and reducing the amount of arc heat input in a GTAW-like application [7].

Advantages of WAAM. Wire Arc Additive Manufacturing (WAAM) has emerged as a compelling production process due to its significant advantages over other manufacturing techniques.

WAAM utilizes a high-power electric arc, enabling deposition rates that can range from 2 to 10 kg/h, significantly expediting the manufacturing of large parts [8]. This high deposition rate is a key factor in its efficiency compared to other additive manufacturing processes like powder bed fusion [5], [7], [9], [10].

The technology benefits from lower initial investment and more affordable production resources, such as standard welding wire and arc welding equipment. The energy efficiency of arc generation in WAAM is notably higher than that of laser and electron-beam methods. Furthermore, the wire feedstock used in WAAM is considerably less expensive than the metal powders required for other AM techniques [5], [11], [12], [13].

WAAM is capable of producing very large components, with dimensions potentially reaching several meters, offering significant scalability for large-scale projects [14].

The layer-by-layer deposition process inherent to WAAM allows for substantial design freedom, enabling the creation of complex and topologically optimized structures with lightweight designs.

As a near-net-shape manufacturing process, WAAM significantly minimizes material waste, especially when compared to subtractive methods. The use of wire feedstock is also more materially efficient than powder-based systems.

WAAM is compatible with a broad spectrum of weldable materials, including various grades of steel, bronze, aluminium, titanium, and nickel alloys.

This technology is highly effective for repairing metal components and adding features to existing parts. This capability extends to on-site repairs, providing a flexible solution for maintenance and part replacement.

WAAM is well-suited for creating Functionally Graded Materials (FGMs), which have varying material properties across a single component. This is achieved by adjusting process parameters or utilizing multiple wires with different compositions, allowing for tailored chemical, microstructural, and mechanical properties.

Compared to powder-based additive manufacturing, WAAM can produce parts with superior mechanical strength at a lower machining cost. It also presents a more cost-competitive alternative to laser-based Directed Energy Deposition (DED) technologies.

Challenges in WAAM. Despite its advantages for production of large-scale metal components, Wire Arc Additive Manufacturing (WAAM) faces several challenges that can impact final product quality and process reliability. These issues primarily stem from the inherent thermal characteristics of the process, geometric inaccuracies, and difficulties in process control.

A primary limitation of WAAM is its lower dimensional accuracy and poorer surface finish compared to other additive manufacturing techniques like powder bed fusion. [3], [7], [10], [11], [15], [16]. This often classifies WAAM as a "near-net-shape" process, necessitating post-processing steps such as machining and heat treatments to achieve the required tolerances and surface quality, particularly for aerospace and structural applications. The reliance on extensive and costly physical experimentation, especially for specialized materials, further complicates process optimization.

The WAAM process generates significant localized heat, leading to steep temperature gradients. This non-uniform heating and cooling results in residual stresses, distortion, and potential cracking [3], [16], [17]. If these stresses surpass the material's ultimate tensile strength, it can lead to fractures [7]. The rapid thermal cycles also create heterogeneous microstructures, often characterized by coarse columnar grains, which can lead to anisotropic mechanical properties. These properties can vary throughout the part, influenced by local cooling rates [3], [7], [18], [19].

Heat accumulation is another significant issue, particularly in smaller parts or as the component height increases. Successive layering reduces heat dissipation to the substrate, which can alter bead geometry and lead to inconsistencies in mechanical properties and microstructure throughout the part. While strategies like increasing the dwell time between layers can mitigate this, they also reduce the manufacturing speed, diminishing one of WAAM's key advantages [20]. Additionally, the intense localized heat can produce metal vapor, raising environmental sustainability concerns [3].

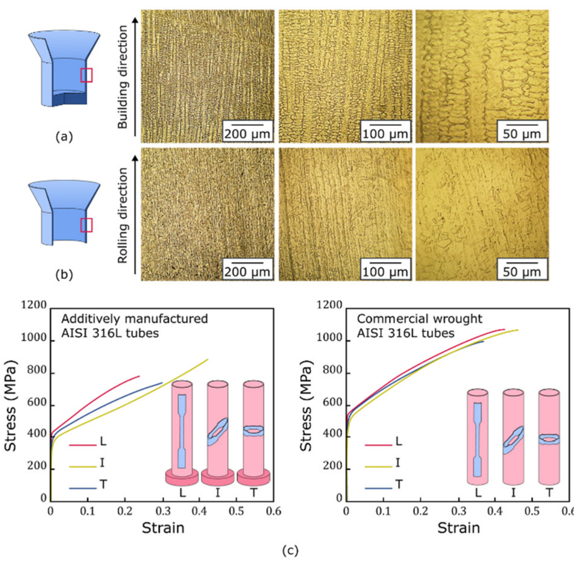


Fig. 4. Influence of WAAM on microstructure and mechanical behaviour of metal parts. Microstructures of metallographic samples taken from (*a*) additively deposited and (*b*) commercial wrought AISI 316L stainless steel tubes. (*c*) Stress-strain curves. Reprinted from [21]

WAAM generally has lower precision and surface quality compared to other AM processes like powder-based methods [3]. It is a near-net shape method, meaning the desired final profile is typically not achieved directly, and the surface finish is often poor with low dimensional accuracy and high surface roughness/irregularities [19]. This often necessitates post-processing steps like machining [14]. Material irregularities can lead to notable reductions in strength and ductility [22]. Larger melt pools can result in reduced end-part resolutions, limiting applicability to simple geometries. Achieving high accuracy in part geometry and repeatability in production is challenging [23].

Porosity possesses a huge challenge in WAAM, especially for Aluminium alloys. During solidification, hydrogen atoms dissolved in the molten pool are expelled from the forming solid phase back into the surrounding liquid. This expulsion occurs due to the substantial differences in hydrogen solubility between the solid and liquid states of the metal [3], [24].

Lack of Fusion occurs when deposited metal does not properly fuse with previous layers or the substrate, often due to insufficient heat input. This leads to structurally weak joints [3], [24].

If residual stresses exceed the ultimate tensile strength, then fracture is expected [7].

Spatter in Wire Arc Additive Manufacturing (WAAM) refers to small metal particles that are ejected from the melt pool or the molten tip of the wire during the deposition process due to arc instabilities. It is a common phenomenon, particularly in Gas Metal Arc Welding (GMAW)-based WAAM, and is considered a defect that can negatively impact the surface quality of a final product [3], [7].

Geometric deviations include defects such as humping (periodic undulations), side collapse, and inconsistent layer height arise from poor heat management and deposition strategies [3], [24], [25].

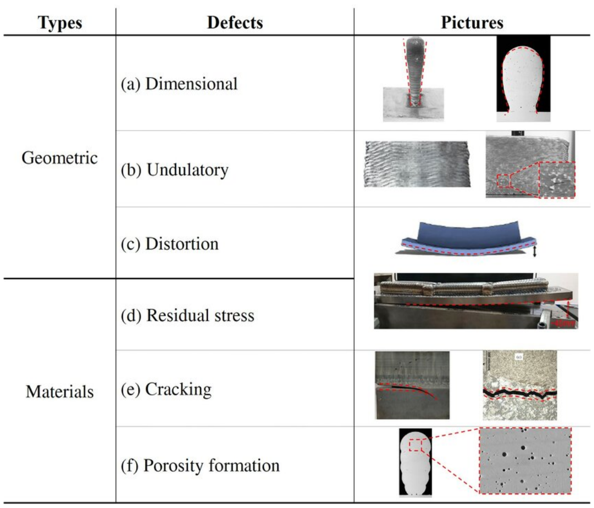


Fig. 5. Defects that may arise in different WAAM technologies and different characteristics of both the material and deviations from the ideal geometry of the final product. Reprinted from [26]

Wire Arc Additive Manufacturing (WAAM) involves numerous interdependent parameters, making process optimization highly complex and prone to variability [7], [15], [19], [25], [27], [28]. This stochastic nature, driven by fluid dynamics, heat transfer, and phase transformations, often leads to a “curse of dimensionality” [29], [30]. Effective control requires deposition and cooling strategies that ensure dense parts, low residual stress, and uniform bead geometry. Poor planning can cause porosity, lack of fusion, or distortion. For example, a tangent overlapping model suggests an optimal bead spacing of 0.738 times the bead width to avoid valleys [7] Other challenges include managing excessive heat sink at the beginning of layers and low heat dissipation at the end. [7] to avoid side collapse.

Monitoring of WAAM process is complicated due to high heat, smoke, and arc light, which limits the effectiveness of sensors like thermocouples and thermal cameras. Issues such as variable emissivity and noisy image-based data further complicate analysis [4], [7], [17], [19], [24], while the lack of standardized data management obstructs quality assurance [11].

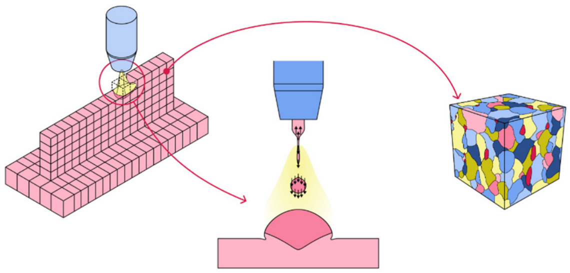
Material choice also constrains WAAM performance. Steels and titanium alloys can exhibit anisotropy due to formation of columnar grains [9], [31]. Aluminium alloys often show reduced toughness due to porosity and solidification defects [28], [32]. High-strength aluminium (e.g., 7xxx series) and certain high-carbon steels are especially prone to hot cracking, limiting their applicability without extensive optimization or post-processing [7]. Limited availability of high-quality material data, especially for specialized metals like Ti–6Al–4V and Inconel 718, is a significant constraint [3], [12], [24], [29].

Numerical Modelling of WAAM

Computer simulations are indispensable for advancing Wire Arc Additive Manufacturing (WAAM), enabling precise predictions of material behaviour, defect formation, deposit morphology and the evolution of residual stressses and distortions. By revealing complex multi-physics phenomena that are hard to probe experimentally, simulation cuts costly trial-and-error, shortens development cycles, reduces material waste, and improves the quality and reliability of WAAM components [3], [9], [16], [24], [33].

The inherent complexity of the WAAM process arises from the interplay of thermal dynamics, fluid flow, phase transformations, and mechanical-chemical behaviours across various scales [3], [16], [24]. To address this, current research employs a multi-scale modelling approach: **macro-scale** (part-level thermo-mechanics, path/parameter optimization, residual stress and distortion prediction), **meso-scale** (bead/layer-level melt-pool hydrodynamics, heat transfer, arc–wire interaction, and bead geometry), and **micro-scale** (microstructure evolution–grain growth, phase changes, precipitation–and resulting properties) Information is exchanged across scales, with meso/micro models informing effective properties and constraints at the macro level, and macro simulations supplying thermal–mechanical histories to drive meso/micro predictions.

Integrating these different scales is a key trend in modern WAAM simulation. The goal is to create a holistic digital framework that connects process parameters with the final performance of the component.



a *b* *c*

Fig. 6. WAAM modelling at the three different scales: *a* – macro, *b* – meso and *c* – micro. Reprinted from [9]

In Wire Arc Additive Manufacturing (WAAM), simulations are vital for ensuring material quality and structural integrity of the final product. Key applications include investigation of material properties and microstructure, layer morphology, distortion and stress, as well as defect detection.

CFD simulations are particularly effective in forecasting the distribution of alloying elements and resulting microstructure, while FEM analyses the full thermal history to estimate strength and hardness. Together, they link process parameters with both microstructural evolution and mechanical performance [3], [7], [24], [34].

Deposit geometry depends on heat input and material properties. Multi-phase CFD models predict melt pool behaviour, droplet impact, and liquid–solid interactions, allowing accurate control of layer height and width while minimizing defects [24], [25], [28].

Thermal cycling in WAAM induces temperature gradients that cause residual stress, distortion, and possible cracking. Thermo-mechanical simulations track stress build-up and guide mitigation strategies. Key factors include phase transformations and stress relaxation [3], [14], [16], [24], [33], [35].

Defect mitigation is a critical challenge in Wire Arc Additive Manufacturing (WAAM), as issues like porosity, cracking, lack of fusion, and distortion can compromise the structural integrity of components. While conventional inspection methods exist, they are often expensive, slow, and limited in capability. To address this, current research leverages numerical simulations (FEM and CFD) to proactively predict and prevent defect formation by modelling heat transfer, melt pool dynamics, and stress evolution [3], [16], [24].

Advanced approaches now incorporate digital twin (DT) architectures with machine learning (ML) and convolutional neural networks (CNNs) for real-time anomaly detection and predictive quality control [29], [30], [37]. By analysing process data from sensors and visual imaging, these intelligent systems can identify and anticipate defects during manufacturing. This allows for immediate adjustments to parameters such as travel speed or wire feed rate, effectively mitigating the formation of flaws.

Thermo-mechanical modelling. This is a macro-scale approach that primarily uses Finite Element Analysis (FEA) to simulate the overall structural temperature variations and distortions of a component [3], [8], [24]. The solution requires the metal part geometry to be discretized into a mesh of three-dimensional elements, linked by nodes, so that calculations resulting from governing equations at element level are assembled into a global system of equations and solved for the entire metal part. The calculations are carried out incrementally (through subdivision of the process time into a series of time increments), and iteratively within a time increment due to the following three main sources of non-linearity: a) Material nonlinearity, b) Changing boundary conditions, c) Geometric nonlinearities.

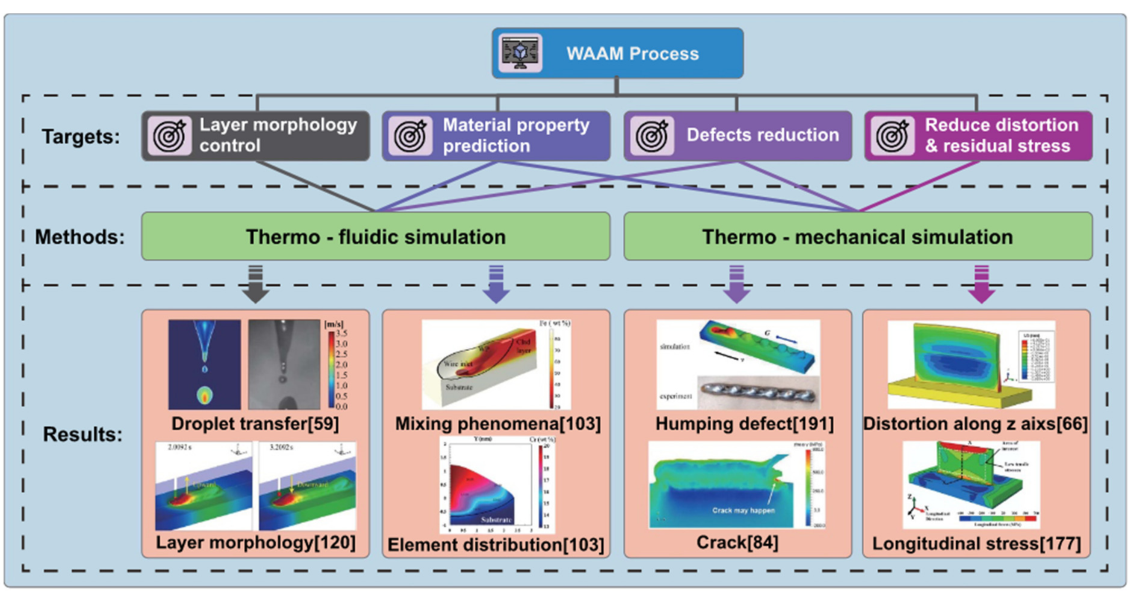


Fig. 7. Applications of different simulation approaches. Reproduced from [36]

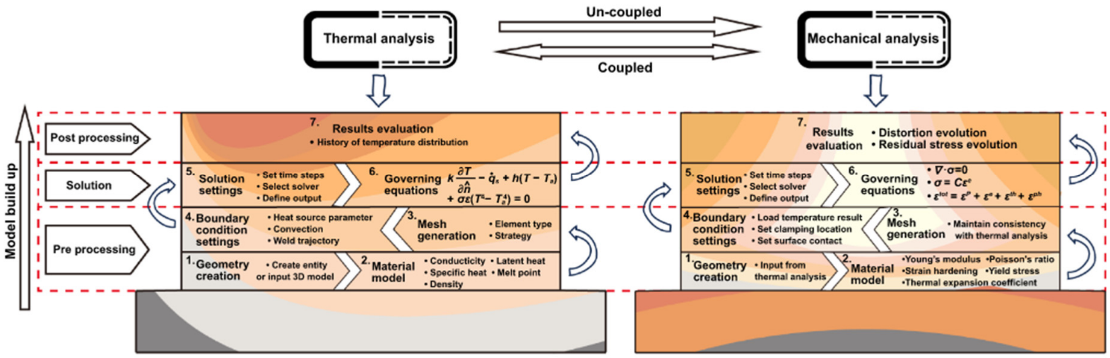


Fig. 8. Typical FEM simulation process. Reprinted from [24]

Thermo-mechanical modelling typically involves three main stages: pre-processing, solution implementation, and post-processing [24].

The most common approach in thermo-mechanical modelling is a sequential coupling method, where the thermal problem is solved first, and the resulting temperature history (and its evolution over time) is then used as an input for the subsequent mechanical analysis [9], [14], [24]. This method assumes that the mechanical response does not significantly affect the thermal field, which makes it computationally efficient for processes where thermal effects are dominant. A fully coupled approach, which solves thermal and mechanical equations simultaneously, exists but demands significantly more computational resources [9], [16].

Definition of model geometry typically involves model from CAD. Details like layer thickness and width are usually derived from slicing software. For simplification, the surfaces of the deposited layers are usually assumed as flat.

Material properties: physical (density, thermal conductivity, specific heat capacity, thermal expansion), mechanical (Young`s modulus, Poisson`s ratio, ultimate and yield stress, ultimate elongation).

Finite element meshing require balance between detailing and computational time. For FE modelling of a dynamic processes such as WAAM, a technique known as Adaptive Mesh Refinement (AMR) or adaptive remeshing is utilized. It involves dynamical adjustment of the finite element mesh, refining it in areas with high thermal gradients and stress, such as the region near the moving heat source. Conversely, it coarsens the mesh in less critical areas where gradients are low, significantly reducing the computational load [24], [38].

To preserve the accuracy of the entire model, particularly in areas left behind by the heat source, a background mesh (BM) is often used to store detailed solution data like stress and strain. While computations are run on the active, refined computational mesh (CM), the results are continuously updated and saved on the BM. Innovative AMR strategies, such as multi-criteria refinement and selective integration, have been developed to further enhance efficiency [24], [38], [40].

The main advantage of AMR is the substantial reduction in computation time and memory requirements compared to conventional Finite Element Method (FEM) simulations that need a uniformly fine mesh. However,

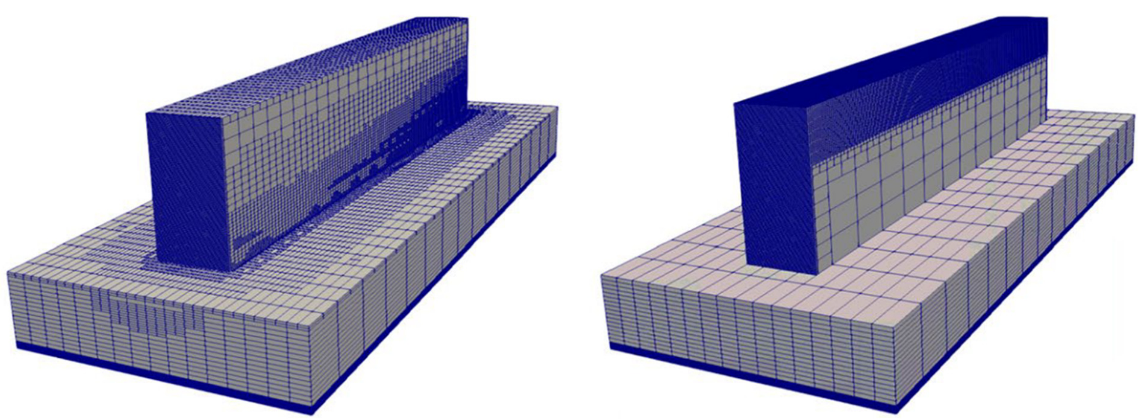


Fig. 9. FE adaptive mesh method. Reprinted from [39]

AMR has its challenges. The initial effort to develop customized meshing strategies can be considerable, and frequent mesh regeneration can, in some cases, increase the solution time. The process of transferring time-integrated variables between different mesh densities requires sophisticated numerical procedures and can be limited to specific element types, which may still lead to a large number of elements for complex parts.

Boundary conditions setting includes thermal boundary conditions (initial temperature, heat escape via convection and radiation) and mechanical boundary conditions (spatial degrees of freedom for structural elements). These can be applied simultaneously or separately, depending on whether the simulation is coupled or uncoupled.

Heat source is commonly idealized by the double ellipsoid model proposed by Goldak *et al*. [41]. This model uses power density distribution functions to simulate the heat source's impact:

$$\dot{q}_v = \frac{6\sqrt{3}\dot{Q}f_{f,r}}{\pi\sqrt{\pi}a_{f,r}bc} exp\left[-3\left(\frac{x^2}{a_{f,r}^2}+\frac{y^2}{b^2}+\frac{z^2}{c^2}\right)\right], \quad (1)$$

where coefficients $a_{f,r}$, b and c are the semi-axes of two ellipsoids with distribution factors $f_{f,r}$ for frontward and backward paths. Alternatively, Ding *et al*. [42] proposed a volumetric heat source model in order to speed up numerical solution.

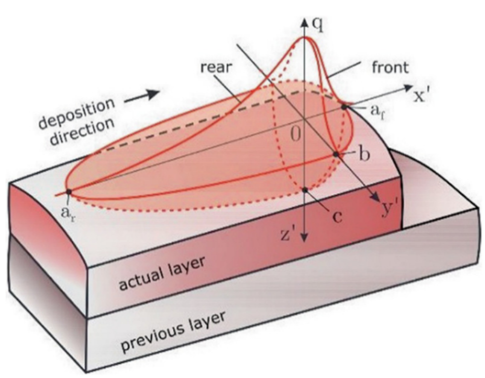


Fig. 10. Goldak heat source model. Reprinted from [43]

In finite element simulations of Wire Arc Additive Manufacturing (WAAM), element activation is crucial to represent material deposition. Two main strategies are used: the Inactive Element Method and the Quiet Element Method.

The Inactive Element Method ("element birth and death") initializes the mesh with all elements present but deactivated, so they temporary excluded from the analysis. As the heat source advances, elements are progressively activated. This reduces computational effort, but requires complex element renumbering and risks adding artificial energy if new nodes inherit existing temperatures [9], [16].

By the Quiet Element Method, elements initially assigned with fictitious properties (e.g., very low stiffness or thermal conductivity) to minimize their influence on the model. When reached by the heat source, these elements switch to real properties. This avoids renumbering and integrates easily with standard FEA, but poorly scaled quiet properties may cause ill-conditioned matrices. Also, residual temperature or stress must be cleared in elements before their activation.

Activation can follow either a temperature-based or time-based criterion. Elements may be activated at melting temperature or above, in which case the heat source calibration must include the energy required to heat filler material upon melting.

Solution of a thermo-mechanical problem is obtained from boundary value problem by simultaneously solving the heat transfer equation (2) and stress equilibrium equation (3)

$$k\frac{\partial T}{\partial \hat{n}} - \dot{q}_s + h\left(T - T_a\right) + \sigma_B \varepsilon\left(T^4 - T_a^4\right) = 0\,, \quad (2)$$

$$\nabla \cdot \sigma + \bar{F} = 0\,, \quad (3)$$

where k is thermal conductivity, T is temperature, $\hat{n}$ is the vector normal to the surface, $\dot{q}_s$ is the heat input rate to the molten pool from the electric arc, h is the heat transfer coefficient, σ_B is the Stefan–Boltzmann constant, ε is the emissivity, σ is stress tensor and $\bar{F}$ is the body force vector.

As an alternative to transient thermo-mechanical analysis, the inherent strain method offers a simplified, quasi-static mechanical analysis. This approach models the local thermo-mechanical distortions from the heat source as 'inherent strains', which are then used as initial conditions in the simulation. This significantly reduces the complexity and computational cost of the analysis [24].

Post-processing involves extracting simulation results (temperature, stress and displacement fields) and their validation by comparing with experimental data. This might include matching temperature history trends measured by thermocouples at specific substrate locations or comparing the size of the melt pool observed experimentally.

Thermo-Fluidic Modelling. Operating at the mesoscale, thermo-fluidic modelling focuses on the transient dynamics of weld pool formation and solidification. This method typically employs Computational Fluid Dynamics (CFD) to analyse complex heat transfer, mass transfer, and free surface fluctuations in the molten pool. It provides detailed, transient multi-physics data that is often difficult to capture experimentally, offering deep insights into melt pool morphology and behaviour.

Thermo-fluidic simulations can predict physical quantities like temperature, fluid flow, and element distribution at millisecond intervals. Unlike Finite Element Analysis (FEA) used in thermo-mechanical models, CFD can predict the final shape of the deposit as it accounts for fluid behaviour like surface tension and viscosity. However, this method is computationally intensive and generally limited to modelling only a few layers of the deposition process due to the significant scale difference between the melt pool and the final component, making it difficult to incorporate global process parameters [24].

The steps, required for thermo-fluidic analysis are shown on Fig. 11.

On Geometry Modelling stage a detailed digital representation of the component to be fabricated is created. To manage computational demands and limit processing time, the spatial boundary of the simulation is typically constrained to the vicinity of the molten pool or confined to a single weld pass, reflecting only a few seconds of the actual deposition process [24].

Physics Modelling step requires definition of following parameters: temperature-dependent material properties (density, internal energy, heat capacity, thermal conductivity, viscosity), heat source idealization (Goldak heat source model, etc.), fluid properties and driving forces.

The liquid metal is usually treated as an incompressible, Newtonian, fluid in laminar flow, simplifying the complexity of the modelling efforts) [3].

The simulation considers two primary categories of driving forces affecting the fluid dynamics, namely body forces (these forces act on the fluid volume itself and include gravitational forces, buoyancy, and surface forces (These act on the free surface of the fluid, including surface tension, Marangoni shear stress, and arc pressure) [3].

Boundary Condition specifies heat flow at the external boundaries and free surfaces to ensure a realistic simulation.

Spatial discretisation involves dividing the computational domain into a mesh of finite elements or volumes. Methods like Finite Volume Method (FVM), Finite Element Method (FEM), or Finite Difference Method (FDM) are used in numerical modelling, with FVM being the most common for CFD [3], [24].

Solution for fluid flow and heat transfer in thermo-fluidic modelling is obtained by simultaneously solving the governing equations based on the laws of physical conservation for mass (4), momentum (5) and energy (6):

$$\frac{\partial(\rho u_i)}{\partial x_i} = 0, \tag{4}$$

$$\frac{\partial}{\partial t}(\rho u_j) + \frac{\partial}{\partial x_i}(\rho u_j u_i) = -\frac{\partial p}{\partial x_j} + \frac{\partial}{\partial x_i}\left(\mu \frac{\partial u_j}{\partial x_i}\right) + S_j, \tag{5}$$

$$\rho\frac{\partial h}{\partial t} + \frac{\partial(\rho u_i h)}{\partial x_i} = \frac{\partial}{\partial x_i}\left(\frac{k}{C_p}\frac{\partial h}{\partial x_i}\right) - \rho\frac{\partial \Delta H}{\partial t} - \rho\frac{\partial(u_i \Delta H)}{\partial x_i}, \tag{6}$$

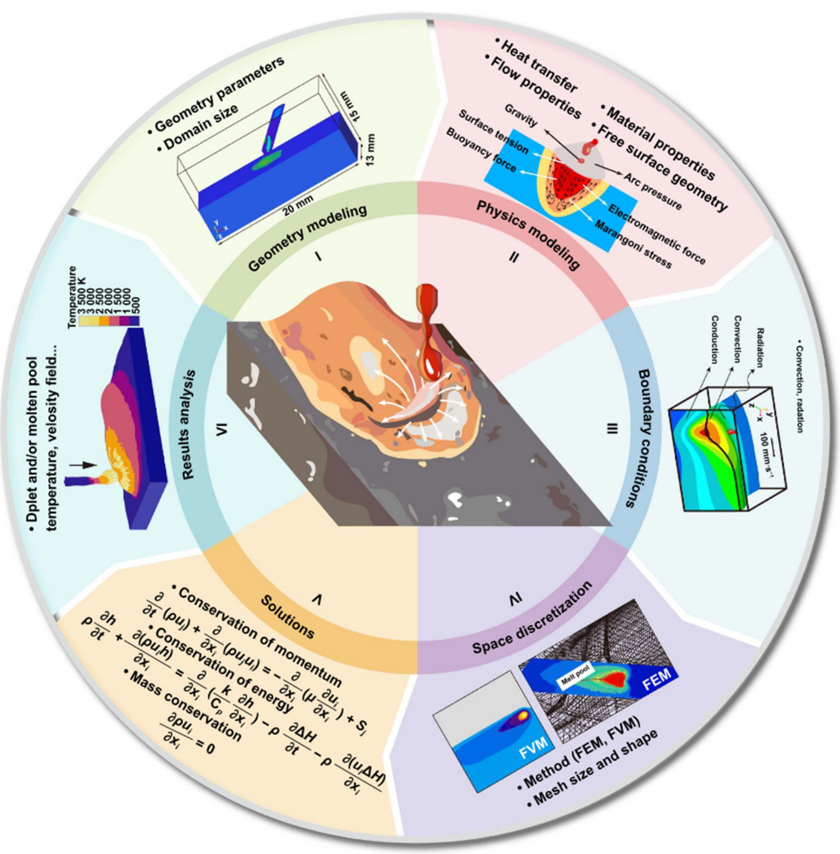


Fig. 11. Typical stages of thermo-fluidic simulation process. Reprinted from [24]

where ρ is the density, u_i and u_j are the velocity components along the i and j directions, respectively, x_i is the distance along the i direction, t is the time, μ is the dynamic viscosity, h is the sensible heat, C_p is the specific heat, k is the thermal conductivity, and ΔH is the latent heat content. The source term S_j considers different driving forces. These equations are solved using appropriate boundary conditions.

Accurate free surface modelling is crucial in thermo-fluidic WAAM simulations to predict melt pool dynamics and layer formation. Several numerical methods address this, balancing cost and accuracy. The Volume of Fluid (VOF) method captures the gas–metal interface, while the Level Set Method (LSM) handles complex geometries. The Enthalpy–Porosity Technique (EPT) models the mushy zone during solidification. Other approaches include Energy Minimization (EM) and the Phase Field Method (PFM), useful for microstructure evolution. Method selection depends on the targeted physical phenomena and fidelity requirements.

The analysis of results from CFD simulations in WAAM includes evaluating the temperature field, velocity field, deposition morphology, and element concentration within the geometry domain. These results are essential for understanding the transient changes in forces or shapes during key processes like droplet formation and molten pool evolution. Due to the reliance on approximations in thermo-fluidic models, validation is crucial. This involves comparing simulation outputs with experimental data under various processing conditions to ensure the models are both accurate and applicable

Other Simulation Approaches. Technological Simulation models the entire WAAM process – including tool paths and wire feed rates – within CAD/CAM systems, predicting part geometry with reasonable accuracy and speed, though errors arise in overlapping zones [44]. Simplified WAAM Simulation (SWS) provides faster, semi-analytical analysis by optimizing deposition sequences through graph-based models. While efficient for thin-walled parts, SWS loses accuracy for bulky components [14]. At the microstructural level, numerical models predict defects and grain evolution using phenomenological, cellular automata, or phase-field methods [24]. Porosity is simulated with Smoothed Particle Hydrodynamics (SPH) for coarse features or bubble models for finer details [3], [24].

Digital Twin Integration in WAAM simulations

Wire-arc additive manufacturing is associated with complex thermal behaviour and material flow which makes bead geometry, microstructure, and defect occurrence highly sensitive to parameter drift and ambient disturbances. High-fidelity physics-based numerical simulations (e.g., FEM/CFD) are invaluable for understanding these phenomena and for process planning, but their computational cost limits their application to simpler and smaller-scale components and makes them unsuitable for real-time applications: complex builds often require hours to days of compute for seconds to minutes of process time [19], [40]. Numerical modelling of complex geometric structures is difficult due to pronounced nonlinearities and unpredictable interactions. Optimal parameter selection is also challenging due to the large number of possible parameter combinations [19]. Consequently, purely physics-based analysis is insufficient when the goal is to keep the process within bounds during fabrication. To overcome these limitations, data-driven and hybrid simulations are used, integrated in Digital Twins (DTs).

A Digital Twin is a computer-generated, virtual replica that accurately depicts a real-world object, system, or process, enabling continuous monitoring, study, and optimization in real time [37], [45] In WAAM, DTs provide a supervisory role, actively maintaining the process within optimal bounds through real-time control commands [46]. They are dynamic systems that continuously update and refine their virtual representation by integrating real-time sensor data from their physical counterparts [24], [46].

The implementation of Digital Twins (DTs) in Wire Arc Additive Manufacturing (WAAM) progresses through three distinct stages, representing increasing level of integration: Digital Model (DM), Digital Shadow (DS) and Autonomous Digital Twin (DT).

At the Digital Model (DM) stage, the focus is on creating a foundational virtual representation of the process and its products, primarily for offline analysis and simulation [47]. This initial step involves developing 3D CAD models of the parts, which can be considered a Digital Twin Prototype (DTP) that encapsulates design information and bills of materials for manufacturing scenarios and validation [45], [48]. To understand the intricate process behaviour, physics-based modelling is extensively employed, including thermo-fluidic and thermo-mechanical modelling, The core objective is to leverage these simulations to explore insights beyond physical experimentation, predict potential defects (like distortion or porosity), and optimize manufacturing strategies before any physical production begins, thereby shortening the qualification period for WAAM parts [24]. Data to inform and validate these models is initially acquired manually from experiments, academic literature, and numerical simulations, also contributing to the training of early machine learning models. Basic 3D visualization tools are used at this stage to interpret the simulation results and conceptualize designs, adding contextual meaning to the generated data [49].

The Digital Shadow (DS) stage is characterized by a unidirectional, real-time flow of data from the physical WAAM system to its digital representation [47], [50], [51]. This means the virtual model automatically updates to reflect the current state of the physical counterpart, enabling continuous monitoring and analysis without direct intervention in the physical process. To achieve this, a wide array of IoT devices and sensors are integrated to collect real-time data of WAAM process, including high-speed sensors like pyrometers and melt pool cameras for temperature, current/voltage sensors, acoustic sensors, spectrometers, and gas flow sensors [30]. Data Acquisition Units (DAUs) play a crucial role in gathering, analysing, and storing this real-time data, often processing it locally at the sensor level (edge computing) to reduce latency and enhance responsiveness [30]. Communication protocols such as Open Platform Communications Unified Architecture (OPC UA) and industrial Ethernet facilitate the seamless and secure streaming of data from physical assets to the digital environment [30], [52]. This real-time information supports monitoring and visualization through interactive dashboards, 3D models, or augmented reality (AR) interfaces for human operators, displaying critical process parameters and machine status [30], [53]. Furthermore, Machine Learning (ML) algorithms, such as Convolutional Neural Networks (CNNs), analyse the incoming sensor data for anomaly detection, identifying defects like oxidation, lack of fusion, porosity, or geometric deformations, and providing insights for predictive maintenance [30], [50], [52]. Although the digital shadow provides real-time insights and flags potential issues, physical system adjustments and corrective actions still require human intervention.

Stage 3, known as the Autonomous Digital Twin or simply Digital Twin (DT), signifies the highest level of integration, characterized by bidirectional, real-time data flow and closed-loop control between the physical and virtual systems. In this advanced stage, the digital counterpart not only continuously monitors and reflects the physical system's state but also possesses the autonomous capability to generate and send real-time control commands to actively guide or modify the physical process [46], [47]. This enables functions such as autonomous decision-making, real-time dynamic control, and process optimization, often leveraging Machine Learning (ML) algorithms and Artificial Intelligence (AI) for predictive and prescriptive analytics [51], [52]. For instance, the system can automatically pause a machine upon detecting high-confidence anomalies or implement adaptive control strategies to compensate for defects and ensure "first-time-right printing" [47]. Essential components include cloud-based modules and servers for processing, storing, and distributing insights, with robust communication protocols like OPC UA ensuring seamless and secure data exchange [11], [30], [47]. Advanced 3D visualization and augmented reality (AR) are providing immersive user interfaces for interpreting complex data, enabling strategic decision-making, and supporting operator training [30], [50]. This comprehensive integration aims to significantly reduce defects, waste, and part qualification times.

From a software architecture perspective, a Digital Twin (DT) is typically structured as a multi-layered or multi-entity framework designed to enable continuous, real-time interaction between a physical asset and its virtual replica. At its core, a DT architecture comprises three elementary components: the Physical Asset (or Observable Manufacturing Element – OME), its Digital Asset (the virtual component or Core Entity – CE), and the Information Flow connecting the two. This information flow is critically bidirectional and automatic for a true Digital Twin, differentiating it from simpler Digital Model or Digital Shadow.

Several frameworks delineate this architecture into distinct layers or entities. For instance, Chen *et al*. [47]. propose a service-oriented framework with four key layers: the Service Layer, defining autonomous functions; the Model Layer, housing physics-based or data-driven (Machine Learning/Artificial Intelligence) models for simulation and prediction; the Data Layer, storing information from various sources in structured databases; and the Interface Layer, managing communication protocols and interactions. Similarly, the ISO 23247 standard [54] outlines five entities: the OME (physical elements), the Data Collection and Device Control Entity (DCDCE) for gathering sensor data and controlling actuators, the Core Entity (CE) managing the DT's operations and hosting analytics/simulation services, the User Entity (UE) for human and enterprise application interfaces, and the Cross-System Entity (CSE) providing common functionalities like data translation and security. In edge computing-based DT (E-DT) frameworks, the DCDCE's role is often expanded to include distributed data processing at the edge, reducing latency and network load, sometimes incorporating edge and cloud data collection sub-entities to streamline data management [53]. Nele et al [51] present a layered framework consisting of a Perception Layer (data acquisition and preprocessing), a Digital Object Layer (forecasting system states and estimating unmeasurable variables), and an Application Analysis Layer (visualization, anomaly detection, control, and optimization).

Key software and technological components embedded within these architectures include IoT devices and sensors for real-time data acquisition; communication protocols like Open Protocol Communication Unified Architecture (OPC UA), industrial Ethernet, or socket communication for secure and seamless data exchange [11], [30], [47], [53]; data storage and management systems, often leveraging cloud-based solutions (e.g., Microsoft Azure Blob Storage), relational (SQL) and non-relational (NoSQL) databases, and data fusion modules for consistent data handling [30], [51], [53]; advanced modelling and simulation software, ranging from 3D CAD models and physics-based tools (Finite Element Method, Computational Fluid Dynamics) to sophisticated data-driven models (Machine Learning, deep learning, Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks) for predictive capabilities [30], [46], [47], [55], [56]; and visualization tools, such as 3D visualization, augmented reality (AR), virtual reality (VR), and interactive dashboards, often implemented using game engines like Unity 3D, to provide immersive and insightful user interfaces [30], [53]. This comprehensive integration, supported by robust cloud and edge computing infrastructure, enables continuous monitoring, diagnostic analysis, and autonomous decision-making, aiming to optimize performance, enhance quality, and reduce costs throughout the asset's lifecycle.

Conclusion

Wire Arc Additive Manufacturing (WAAM) offers a practical route to large, structurally efficient metal components with attractive economics and lead times. Despite these advantages, WAAM remains challenged by issues such as residual stress, geometric inaccuracy, and defects. The integration of advanced computational simulations—including thermo-mechanical, thermo-fluidic, and hybrid modelling—provides a powerful toolkit to predict and optimize thermal behaviour, material properties, and structural distortions. Techniques such as adaptive mesh refinement (AMR) have proven to significantly enhance simulation efficiency without compromising accuracy.

Mature FEM/CFD frameworks can now reproduce temperature histories, bead geometry, and stress fields with useful fidelity, but their runtimes and input sensitivities limit in-process deployment. Emerging DT implementations mitigate these constraints by pairing validated mechanistic cores with fast predictive models and in-situ sensing, enabling inter-pass temperature management, bead-height stabilisation, and early distortion forecasts. Across studies, robust calibration against thermal imaging, process electrical signals, and profilometry remains decisive for credible predictions.

From this synthesis, the following guidance emerges for practice: (1) define the operational goal (monitoring, prediction, or closed-loop control) and set targets for latence/accuracy; 2) select model scale, heat-source representation, and material laws consistent with those goals; 3) adopt a minimal yet informative sensing stack and perform continuous calibration; 4) quantify uncertainty and propagate it to decisions; and 5) ensure traceability via a clear digital thread.

Key gaps persist: the lack of standardised, shareable datasets and benchmarks; limited handling of domain shift across materials, geometries, and equipment; incomplete uncertainty quantification; and weak coupling between modelling, path planning, and residual-stress-aware control. A near-term roadmap prioritises open datasets and metrics, physics-guided learning with uncertainty bounds, domain-adapted calibration, faster multi-scale coupling, and controller co-design. Addressing these items will accelerate qualification and move WAAM towards repeatable, certifiable production in industrial environments.

Conflict of interest

The authors declare that they have no conflict of interest with respect to this research, including financial, personal, copyright, or any other conflicts that could influence the research and its results presented in this article.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technology in the creation of this work.

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Чисельне моделювання та цифрові двійники в адитивному виробництві з використанням дугового наплавлення (WAAM)

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Анотація. *Адитивне виробництво з використанням дугового наплавлення (WAAM) стало цінним інструментом для економічно ефективного виробництва великих металевих конструкцій зі складною геометрією з використанням відпрацьованого обладнання для дугового зварювання та дротяної сировини. Однак складність фізичних процесів, що лежать в основі цього процесу, ускладнює прогнозування геометрії та напружено-деформованого стану кінцевих виробів. Накопичення тепла, температура між проходами та планування траєкторії впливають на форму наплавленого валика та утворення дефектів, тоді як циклічне термічне навантаження викликає залишкові напруження та деформації, що перешкоджають повторюваності та сертифікації. Високоточне чисельне моделювання, хоча і є важливим для вивчення та оптимізації процесу WAAM, залишається непридатним для моделювання та контролю в реальному часі через високу обчислювальну вартість. З метою подолання обмежень моделей, що базуються виключно на фізиці, інтерес перейшов до гібридних робочих процесів – комбінованих моделей, що базуються на фізиці та даних, каліброваних за допомогою датчиків в реальному часі, – вбудованих в архітектуру цифрового двійника (Digital Twin, DT) для підтримки прогнозування, моніторингу та контролю процесів. Метою цього дослідження є систематизація останніх досягнень у багатомасштабному мультифізичному чисельному моделюванні для адитивного виробництва з використанням дугового зварювання (WAAM) та надання інформації про архітектури цифрового двійника (DT) поряд з підходами на основі даних, заснованими на штучному інтелекті (AI), машинному навчанні (ML) та управлінні даними. Було проведено широкий огляд літератури з метою виявлення переваг та обмежень цих методів моделювання, а також впровадження їх у процес WAAM для досягнення розумного виробництва, що базується на потоках даних, з моніторингом у реальному часі, аналітичним прогнозуванням та автономним корегуванням. Результати огляду можуть бути використані в майбутніх дослідженнях для організації та складання розумних систем WAAM в лабораторних експериментальних умовах з перспективою подальшого промислового застосування.*

Ключові слова: *Адитивне виробництво з використанням дугового наплавлення (WAAM), 3D-друк, FEM (МСЕ), CFD, цифровий двійник, залишкові напруження, деформації, виявлення дефектів.*