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A review on physics-informed machine learning for monitoring metal additive manufacturing process

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Abstract: The traditional data-driven models and pure physics models have been widely employed in quality prediction for additive manufacturing (AM). However, data-driven models rely on a large amount of labeled data, while pure physics models suffer from lower computational efficiency and accuracy. The Physics-Informed Neural Network (PINN) model has emerged as a hybrid data-driven paradigm that imbues data-driven models with physical domain knowledge. To refrain from the inherent "black box" or inefficiency of AM process prediction or monitoring, this paper discusses the pros and cons of traditional data-driven methods and pure physics models and further elaborates on the principles and architecture of the PINN model along with its applications in AM research. We review and analyze current state-of-the-art PINN applications to AM, focusing on temperature field prediction, fluid dynamics issues, fatigue life prediction, accelerated finite element simulation, and process characteristics prediction. The corresponding embedded physical knowledge, either integrated into loss function or data preprocessing, is also summarized for these applications. Based on this review, we identify the challenges of PINN and provide an outlook for further research of its AM applications.

Keywords: Data-driven models; physics models; additive manufacturing; physics-informed neural network

1. Introduction

Contrary to subtractive manufacturing, which involves removing excess material from bulk to form final parts or products, additive manufacturing (AM) builds solid components using a layer-by-layer approach[1], offering features such as rapid fabrication of complex parts, shortened product development cycles, accelerated product iteration, material diversity, and high material utilization rates. A huge advantage makes additive manufacturing a promising emerging manufacturing technology[2]. Common additive manufacturing techniques[3] include 3D printing, selective laser melting, powder bed fusion, and directed energy deposition. Leveraging its advantages such as design flexibility, material savings, and production efficiency, AM has been widely applied across various industries including aerospace, automotive, healthcare, manufacturing, construction, energy, and military defense[4]. AM has driven innovation, optimized production processes, and met the growing market demand for personalized and customized products. However, the fabrication quality of components in the additive manufacturing process is influenced by various critical factors, for example, the precise control of process parameters and stable temperature field. During the additive manufacturing process, improper setting of process parameters or inaccurate temperature control may lead to issues such as porosity, cracks, interlayer separation, and inconsistent surface roughness in components. These problems not only affect the visual quality of the components but, more importantly, can significantly impact their mechanical performance and service life. To address these challenges, traditional approaches including data-driven machine learning (such as neural networks) and physics-based methods (such as finite element analysis) can achieve comprehensive monitoring and optimization of the additive manufacturing process.

Data-driven machine learning[5–7] relies on extensive historical data to reveal the complex relationships between input variables and target variables. When direct physical models are difficult to establish or fail to accurately describe the interactions between variables, these methods can assist us in establishing mapping relationships from inputs to outputs by learning patterns in the data, thereby constructing models to predict future trends or behaviors[8]. Through training, data-driven machine learning models can capture nonlinear features and deep-level interactions in the data, providing us with a powerful tool to address problems that traditional analytical methods struggle to handle. Data-driven machine learning models have found extensive applications in additive manufacturing [9,10], particularly in defect prediction, process optimization, and material selection, significantly enhancing manufacturing efficiency and product quality. Nevertheless, critical limitations persist. These models often disregard the constraints imposed by physical laws, resulting in inadequate generalization ability when confronted with novel or unseen data. Additionally, they heavily rely on large-scale, high-quality datasets, which are typically time-consuming and expensive to collect, posing considerable challenges in data acquisition and processing. The lack of interpretability in data-driven machine learning models complicates the comprehension of the underlying principles governing prediction outcomes. Neural network models demonstrate poor transferability across diverse scenarios, thus limiting their broad applicability[11]. Finally, the high computational resource requirements, especially in deep learning models, may present challenges in resource-constrained environments.

The physics-based methods fundamentally involve establishing detailed physical models to simulate phenomena such as heat conduction, melt pool behavior, and stress distribution during additive manufacturing processes[12]. This method offers profound physical insights, aiding in the optimization of process parameters to reduce the occurrence of defects. However, the application of traditional pure physical methods in the field of additive manufacturing also exhibits significant limitations. Although traditional physical methods can provide highly accurate predictions based on physical laws, they typically require substantial computational costs and precise parameter calibration, making them unsuitable for online control and iterative design applications. The computational fluid dynamics (CFD) model[13] can consider heat transfer and fluid flow within components, but its computational costs are high, and it typically operates only at the mesoscale[14]. While the finite element method (FEM)[15] boasts lower computational costs, it remains excessively time-consuming for time-sensitive applications[16], such as online process control, failing to meet the demands of Industry 4.0 for rapid and near real-time simulation.

To address the limitations observed in both data-driven machine learning models and traditional physics-based methods in the field of additive manufacturing, we propose a solution driven by both physical knowledge and data, physics-informed neural networks (PINNs)[17]. The essence of PINNs lies in integrating physical knowledge from the additive manufacturing domain into data-driven models, thereby constructing machine learning models that are physically sound, mathematically accurate, and computationally stable and efficient. In the field of additive manufacturing, PINNs have gradually gained widespread application for addressing key issues such as temperature distribution prediction, fluid flow velocity, parameter identification, and process control in manufacturing processes, demonstrating significant advantages. PINNs combine physical principles with data-driven methods, making them more aligned with the underlying physical laws compared to purely data-driven machine learning methods. Moreover, they offer higher predictive accuracy than traditional physics models, ensuring the physical consistency and accuracy of model predictions. PINNs can provide parameterized solutions, making them highly suitable for sensitivity analysis and optimization tasks. During both training and prediction processes, PINNs can be trained and predicted rapidly and inexpensively, reducing reliance on large amounts of labeled data. Additionally, they outperform traditional methods such as machine learning and finite element methods in terms of computational costs, while also providing better interpretability and generalization capabilities. Especially in scenarios requiring real-time or near-real-time decision support, PINNs enhance understanding and control of complex manufacturing processes by effectively integrating physical knowledge. Consequently, PINNs provide powerful tools for quality assurance and process optimization in additive manufacturing. By utilizing real-time data collection analysis and physics knowledge, coupled with advanced algorithms and models, it is possible to accurately predict the thermal history and potential defects of components, thereby achieving precise control of component quality. This not only helps improve the quality and precision of components but also enhances production efficiency, reduces costs, and promotes the wider application of additive manufacturing technology.

The rest of this paper is organized as follows. The second part describes the architecture of the PINN model and addresses fundamental issues and research strategies regarding the integration of physical knowledge into neural networks. The third part explores the extensive applications of the PINN model in the field of additive manufacturing. The fourth section discusses the challenges and outlooks currently faced by the PINN model and the potential limitations in its application to additive manufacturing.

2. Physics-informed AM

2.1. Physical knowledge embedding strategy

To address the limitations of data-driven approaches and traditional physics-based methods, an effective solution is to use the knowledge accumulated in the additive manufacturing industry for many years to build a dual-driven model of knowledge and data to improve the accuracy and robustness of the model and reduce the demand for data. As depicted in Figure1, combining professional knowledge, experimental data, and machine learning technology in the field of AM, an efficient intelligent framework can be constructed to accurately predict and optimize various complex phenomena in the AM process. The domain knowledge in AM includes the physical phenomena and mechanisms occurring during additive manufacturing, fundamental physical laws such as conservation of mass, momentum, and energy, heat conduction equations, fluid dynamics equations (*e.g.*, Navier-Stokes equations), and other energy transfer equations. It also encompasses the physical conditions at the boundaries and initial states of the system, such as fixed boundaries, free boundaries, convective boundaries, and initial conditions like temperature distribution and velocity fields. This research strategy employs knowledge embedding methods, utilizing the strong fitting ability of machine learning to describe the high-dimensional complex mapping relationship between variables, and combines physical prior knowledge to ensure that the prediction results conform to the physical mechanism. The methods of knowledge embedding encompass embedding complex forms of control equations into the model, integrating general knowledge outside the control equations, and incorporating knowledge of irregular physical fields into the model, as depicted in Figure2. For example, Ness *et al*.[18] introduced physical-based features in the data preprocessing stage, enabling machine learning models to capture heat transfer patterns during AM processes for predicting thermal histories in unknown scenarios. A physical information and data-driven method proposed by Kats *et al*.[19] helped understand the evolution of grain structure during additive manufacturing. Such an approach used physical-based local features (*e.g.*, temperature gradient and cooling rate) as input to predict and control the grain structure characteristics during directional energy deposition (DED). Additionally, an adaptive strategy can be employed by modifying the weights of regularization terms in the loss function, enabling better adaptation to diverse scenarios. When constructing a PINN model, a direct and commonly used strategy involves incorporating the physical partial differential equations (PDEs), initial conditions (ICs), and boundary conditions (BCs) of the research problem into the loss function to ensure that the generated solutions adhere to established physical laws[16]. The following section focused on how to embed knowledge into the loss function to construct the PINN framework.

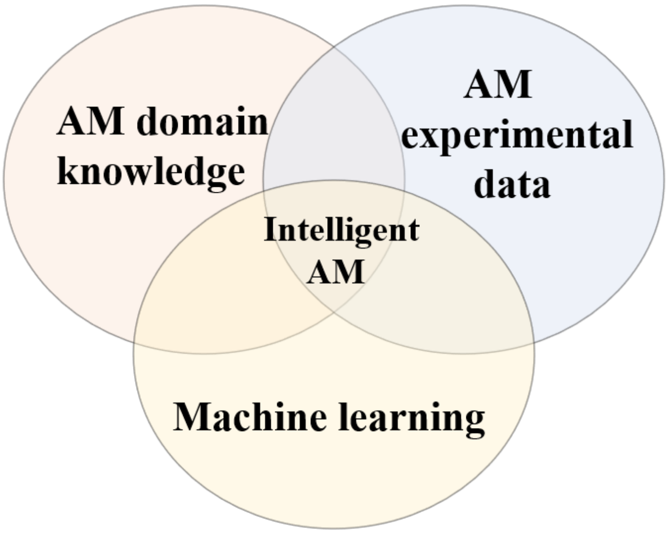

Figure 1. The Intelligent framework combining AM domain knowledge, experimental data, and machine learning.

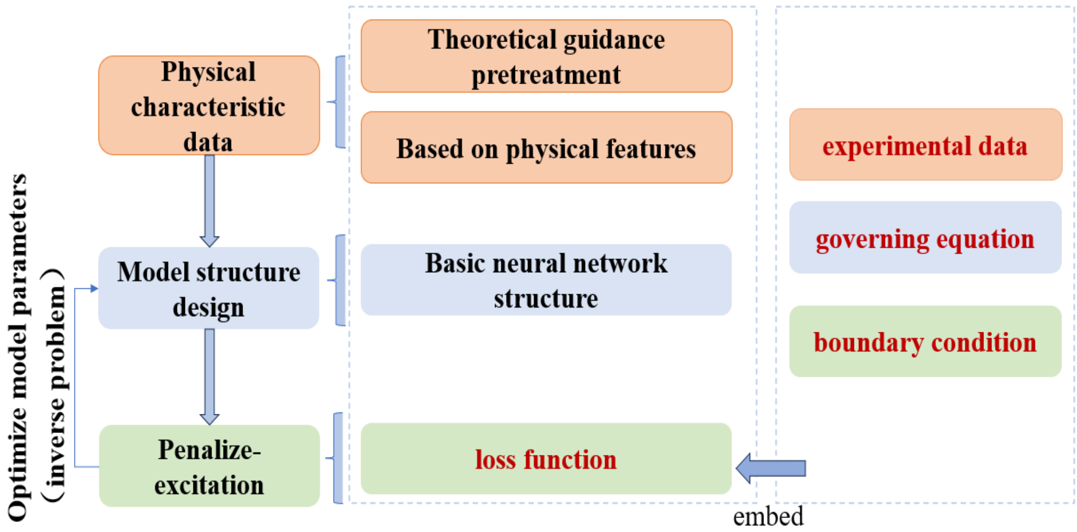

Figure 2. The schematic diagram of the knowledge embedding method for the whole process of machine learning modeling.

2.2. PINN fundamentals

The construction process of the PINN framework began with the selection of an appropriate foundational neural network. Subsequently, based on the specific physical characteristics of the research problem, relevant PDEs along with their boundary conditions were chosen. Finally, these physical insights were ingeniously integrated into the neural network's loss function. This framework enabled the model to adhere to physical laws while fitting experimental data, ensuring consistency between predicted results and physical principles, thereby enhancing prediction accuracy.

2.2.1 Neural network basis

As the core component of the PINN model, the basic neural network is responsible for learning and approaching the behavior of the physical system. Considering that the essence of PINN is also to solve complex partial differential equations, it is essential to consider the dimensions of the problem, the complexity of the network, and the required fitting capability when selecting the fundamental neural network. The fully connected neural network is widely utilized as the foundational architecture of PINN due to its relatively simple network structure, enabling flexible learning of complex relationships among input data. Furthermore, within the PINN framework, the network structure can be adjusted as needed to approximate solutions for partial differential equations, thus leading to its extensive application as the fundamental structure of PINN models. The PINN model developed by Liao and Xue[14] to predict temperature fields consists of three hidden layers, each comprising 64 neurons, of which the input layer has 4 neurons, corresponding to the four dimensions of the input spacetime coordinates. To ensure the predicted temperature values stay positive, the Softplus activation function is applied to the output layer, while hyperbolic tangent (tanh) activation functions are used in all other hidden layers. However, as the number of hidden layers increases, training becomes difficult due to issues such as exploding or vanishing gradients. Therefore, a residual block[20] was added to the network. By incorporating identity mapping, which added the output of the previous layer to the output of the current layer, residual neural networks improved the stability and convergence speed of model training. Incorporating this characteristic, the structure of the PINN model developed by Li and Wang[16] was a residual neural network with 30 neurons and 1 residual block. Yazdani *et al*.[21] employed convolutional neural networks (CNNs) to learn velocity and pressure fields in fluid dynamics. This demonstrated that CNNs can also serve as foundational models for PINNs, capable of handling spatially correlated data.

In addition to the commonly used fully connected neural networks, other neural network architectures, such as CNNs, recurrent neural networks (RNNs), and long short-term memory networks (LSTMs), can serve as foundational models for PINNs. Furthermore, integrating advanced architectures into PINNs to address various problems involving partial differential equations. For instance, Transformer networks are more effective than traditional RNNs or LSTMs at capturing long-range dependencies. Within PINNs, Transformers can handle spatiotemporal data in AM processes, such as monitoring the deposition process over time and space. Additionally, Graph Neural Networks (GNNs) can model the complex geometries of AM parts, ensuring adherence to physical laws through PINNs. Moreover, Variational Autoencoders and Generative Adversarial Networks can generate data while PINNs impose physical constraints, which is highly beneficial for design and optimization tasks. In general, the corresponding type of neural network could be selected to construct the PINN model according to the characteristics of the problem.

2.2.2 Governing equations

The governing equations serve as the cornerstone for problem-solving and are also integral components in the construction of the PINN model. According to the specific solution problem, it is very important to choose the appropriate governing equations. These control equations were embedded into the loss function to ensure that the neural network model can follow the physical laws in the training process. For instance, when solving the problem of predicting the temperature field distribution in AM, the heat conduction modeling was carried out under the condition of considering the convective heat transfer of fluid flow and ignoring the heat loss of vaporization. The transient heat conduction differential equation in AM is expressed as follows:

$$\rho C_P \frac{\partial T}{\partial t} + \nabla \cdot q = 0 \tag{1}$$

$$\rho C_P \frac{\partial T}{\partial t} = -\nabla \cdot q + q_{laser} \tag{2}$$

where ρ represents the material density, Cp denotes the material's heat capacity, T stands for temperature, t signifies time, q represents heat flux, ∇ denotes the gradient operator, and q_{laser} represents the energy generated per unit volume by the laser heat source.

Eq. (1) and (2) both describe the energy balance in the process of heat conduction, but they are applicable in slightly different scenarios. Eq. (1) specifically addresses heat conduction without internal heat sources, where changes in heat are solely determined by the divergence of the heat flux. This scenario is applicable when heat changes only through the conductive action of the material. In contrast, Eq. (2) incorporates an additional internal heat source term, suitable for situations where there are extra heat sources or heat flows within the system. In this model, the change in heat is influenced not only by the divergence of the heat flux but also by the direct impact of the internal heat sources. This makes Eq. (2) more broadly applicable and practical in dealing with complex heat conduction problems. Furthermore, the choice of the physical differential equation is closely related to the boundary conditions. If the heat source is considered only as part of the boundary conditions and not as an internal component of the system, Eq. (1) is typically used to describe the heat conduction process. For example, when considering one side of a material exposed to an external environment that provides a constant heat flow, this external heat flow can be viewed as a boundary condition, eliminating the need to explicitly consider an internal heat source in the differential equation. However, if there are indeed additional internal heat sources, and these sources are not merely part of the boundary conditions, Eq. (2) is usually required to describe the heat conduction process of the system more accurately. This approach allows for a more comprehensive consideration of various internal and external factors affecting heat conduction, thereby providing more precise analysis and prediction.

The law describing the transfer of heat through heat conduction in matter is given by Fourier's law:

$$q = -k\nabla T \tag{3}$$

Where k represents the material's thermal conductivity, ∇T denotes the temperature gradient, which is a vector field representing the rate and direction of temperature change in space.

$$\nabla T = \left(\frac{\partial T}{\partial x}, \frac{\partial T}{\partial y}, \frac{\partial T}{\partial z} \right) \tag{4}$$

Specifically, the governing equation of heat conduction can be expressed as:

$$\rho C_P \frac{\partial T}{\partial t} = k\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} \right) \tag{5}$$

The corresponding initial conditions are:

$$T(x,0) = T_0, x \in \Omega \tag{6}$$

At the initial time t=0, the initial temperature distribution of the temperature field T throughout the entire region is T_0. Due to the absence of preheating on the substrate, the initial temperature T_0 equals the ambient temperature. Among them, x, y, and z are spatial coordinates, and t is the temporal coordinate. Together, they form the spatiotemporal coordinates. For instance, in a PINN model addressing the heat conduction problem, the input (x, y, z, t) represents the spatiotemporal coordinates of a specific point in space (x, y, z) at time t.

The thermal flux boundary conditions during the AM process can be described as follows, neglecting the material's latent heat of fusion and latent heat of vaporization[14].

$$q \cdot \vec{n} = q_{laser} + q_{conv} + q_{rad} \tag{7}$$

Where q represents the total heat flux passing through the surface, and n is the surface's normal vector. Combining with Eq. (3):

$$-k\frac{\partial T}{\partial \vec{n}} = q_{laser} + q_{conv} + q_{rad} \tag{8}$$

Where q_{laser} represents the heat generated by the laser heat source, q_{conv} denotes the heat generated by convective heat transfer, and q_{rad} signifies the heat generated by radiative heat transfer.

The laser heat flux was modeled using a Gaussian surface heat flux model:

$$q_{laser} = -\frac{2\eta P}{\pi r_b^2}\exp\left(\frac{-2d^2}{r_b^2} \right) \tag{9}$$

Where η is the laser absorptivity, P is the laser power, r_b is the radius of the laser beam, and d is the distance from the material point to the center of the laser. The formula for convective heat flux calculation is:

$$q_{conv} = h_c(T - T_0) \tag{10}$$

Where h_c is the convective heat transfer coefficient between the substrate and air, T is the temperature, and T_0 is the ambient temperature. The formula for calculating radiative heat flux is as follows:

$$q_{rad} = \sigma\varepsilon(T^4 - T_0^{\ 4}) \tag{11}$$

Where σ is the Stefan-Boltzmann constant, ε is the emissivity, and T_0 is the ambient temperature.

In the PINN model, the determination and implementation of initial and boundary conditions are indeed crucial, as they directly impact the model's accuracy and physical consistency. Initial conditions typically describe the state of the system at the beginning of the time domain, while boundary conditions describe the behavior of the system at the spatial boundaries. The necessary initial and boundary conditions can be determined based on the physical laws governing the problem. For instance, in a heat conduction problem, the initial condition would be the temperature distribution of the object at the initial time, while the boundary conditions would be the temperature or heat flux distribution on the object's surface. Moreover, in certain special cases, initial and boundary conditions can be obtained through experimental measurements or other observational data. These data can be directly used as the initial or boundary conditions for the PINN model or as part of the training data to satisfy the constraint conditions. By doing so, the PINN model can better reflect the behavior of the actual physical system and improve the model's predictive accuracy.

In addition, when addressing temperature and melt pool fluid dynamics prediction in the AM process, the governing equations for thermal fluid flow during the AM process can be simultaneously described via momentum conservation equation, mass conservation equation (continuity equation), and energy conservation equation, as shown below:

$$\rho\left(u,t + u\cdot\nabla u - g\right) + \nabla p - 2\mu\Delta u = 0 \tag{12}$$

$$\nabla\cdot u = 0 \tag{13}$$

$$\left(\rho C_P T\right),t + u\cdot\nabla\left(\rho C_P T\right) + \left(\rho L f_L\right),t + u\cdot\nabla\left(\rho L f_L\right) - k\nabla^2 T - Q_T = 0 \tag{14}$$

Where u represents the velocity field, p denotes the pressure field, g is the gravitational acceleration vector, ρ and μ are the density and dynamic viscosity respectively, C_p is the specific heat capacity, L is the latent heat, κ is the thermal conductivity, Q_T denotes the energy source term, and f_L represents the liquid phase fraction. The initial conditions and boundary conditions are defined for the above control equations, which ensure the well-posedness of the system and follow the Dirichlet and Neumann boundary conditions.

$$u = u_{bc} \tag{15}$$

$$p = p_{bc} \tag{16}$$

$$T = T_{bc} \tag{17}$$

$$-pn + 2\mu\nabla^S u \cdot n = \tau \tag{18}$$

$$k\nabla T \cdot n = q \tag{19}$$

Where u_{bc}, p_{bc}, and T_{bc} are the velocities, pressures, and temperatures prescribed on the Dirichlet boundaries, while τ and q represent traction and heat flux specified on the Neumann boundaries. ∇^S is a symmetric gradient operator, and n is the unit normal vector on the boundary.

Generally, the PINN model exhibits high flexibility, requiring the determination of appropriate governing equations based on specific problems, typically presented in the form of partial differential equations. In the modeling process, it is essential to comprehensively consider boundary conditions, initial conditions, and the solvability of equations to ensure that the model accurately reflects physical phenomena and obtains feasible solutions.

2.2.3 PINN model

Physical neural networks have been developed to solve the forward and inverse problems of all or part of the known control equations[17,22]. In the PINN model, incorporating known PDEs as constraints enables the neural network to learn the dynamic behavior of the system. Consequently, even in the absence of complete data or complex physical models, PINN can effectively solve forward problems, such as predicting the system's behavior based on thermal conduction differential equations to forecast thermal history. An inverse problem involves inferring the system's parameters or initial conditions from partial outputs or states of the system. By combining observational data with PDEs, neural networks can infer unknown parameters of the system. For instance, by observing the stress-strain relationship of a material and applying the elasticity equation, PINN can deduce the material's elastic modulus and other parameters. Incorporate partial differential equations, initial, and boundary conditions into the loss function. The core idea of PINN is to utilize neural networks to approximate solutions to partial differential equations. It is trained by minimizing the loss function defined based on the residuals of partial differential equations, boundary conditions, initial conditions, and actual data. In the absence of additional labeled data, the loss function comprises three residual terms for PDEs, BCs, and ICs. Taking the heat conduction problem as an example, different physical residuals can be described as follows:

$$R_p = \rho C_P \frac{\partial T}{\partial t} - k\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2}\right) - q_{laser} \tag{20}$$

$$R_i = u(x,0) - T_0 \tag{21}$$

$$R_b = k\frac{\partial T}{\partial \vec{n}} - \left(-\left(q_{laser} + q_{conv} + q_{rad}\right)\right) \tag{22}$$

When additional labeled data is introduced, the loss term based on labeled data can be added to the total loss, with its residual term as follows:

$$R_d = u\left(x^d, t^d\right) - u\left(x^d, t^d\right) \tag{23}$$

Where $u(x,0)$ represents the model's predicted output at *t=0*, $u\left(x^d, t^d\right)$ denotes the model's predicted output when the input is *x* and *t*, and $u\left(x^d, t^d\right)$ represents the actual experimental output of the process data at coordinates *x* and *t*.

In each iteration, each loss term can be computed at its respective sampling point：

$$L_p = \frac{1}{N_p}\sum_{i=1}^{N_p} R^2{}_P \tag{24}$$

$$L_i = \frac{1}{N_0}\sum_{i=1}^{N_0} R^2{}_i \tag{25}$$

$$L_b = \frac{1}{N_b}\sum_{i=1}^{N_b} R^2{}_b \tag{26}$$

$$L_d = \frac{1}{N_d}\sum_{i=1}^{N_d} R^2{}_d \tag{27}$$

When no additional labeled data is introduced, the total loss function consists of three terms:

$$L_{\text{total}} = \lambda_p L_p + \lambda_i L_i + \lambda_b L_b \tag{28}$$

When introducing additional labeled data, the total loss function consists of four terms:

$$L_{\text{total}} = \lambda_p L_p + \lambda_i L_i + \lambda_b L_b + \lambda_d L_d \tag{29}$$

Where N_p, N_0, N_b, and N_d are the sampling points for different physical equations, and λ_p, λ_i, λ_b, and λ_d are their corresponding weights. The key step in calculating PDE is the calculation of partial derivatives. The PINN model employs automatic differentiation (AD) as its computational method, which is commonly used in deep learning and widely applied in neural networks. In the example of predicting temperature distribution, the differential equation of heat conduction is embedded in the loss function, and Figure3 presents the schematic diagram of PINN architecture.

In the absence of labeled data, the training process of a PINN primarily relies on physical computations derived from PDEs. However, the learning capability of the underlying neural network remains crucial in this context. The network's ability to learn effectively determines its capacity to approximate the solution function that satisfies the physical constraints. In the presence of labeled data, the neural network must not only satisfy the physical constraints but also fit the data, thereby enhancing prediction accuracy and reliability. This imposes greater demands on the network's expressive power and optimization capability.

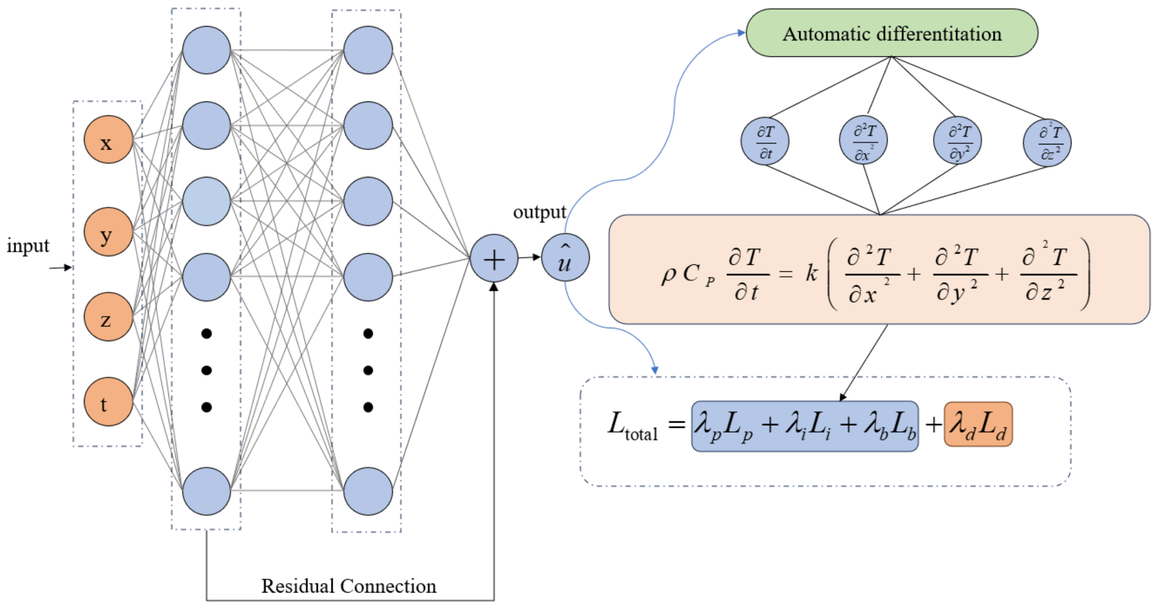

Figure 3. PINN architecture schematic diagram.

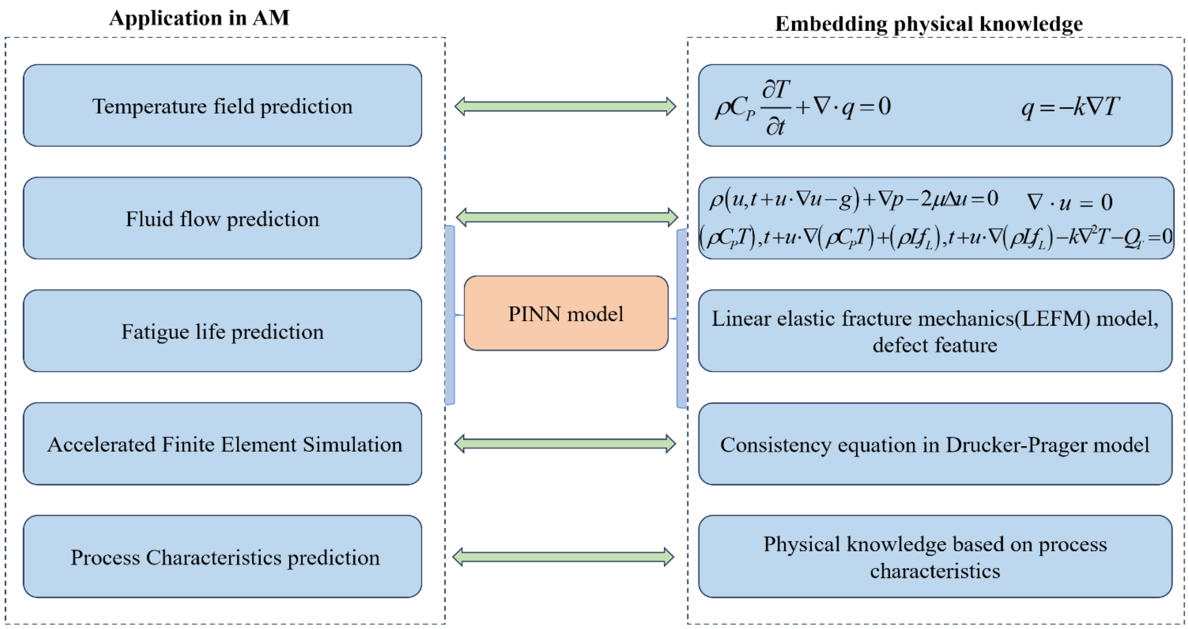

Figure 4. PINN models applied to AM.

3. Application of PINN to AM

Recently, PINN combined with prescribed physical laws[17] has been widely employed in AM to address multiple problems. Here, we review some relevant studies on the application of PINN models in AM, primarily focusing on predicting temperature field distribution, fluid dynamics issue, process characteristics prediction (such as melt pool size and porosity), and fatigue life, as well as their applications in accelerating finite element simulation. Figure 4 summarizes the PINN models in the AM application and the corresponding physical knowledge.

3.1. Temperature field prediction

In contrast to traditional neural network models that relied on infrared cameras for capturing temperature images as inputs, the PINN model utilized spatial and temporal coordinate data, with predicted temperature values serving as outputs. It employed a four-layer fully connected neural network and was trained using FEM simulation data, avoiding the need for complex experimental procedures. The loss function was ingeniously defined as a combination of heat conduction PDEs, heat flow BCs, and ICs, as well as additional data-driven loss terms. This enabled accurate prediction of temperature values at specified spatiotemporal coordinates, thereby inferring the three-dimensional temperature distribution history. A hybrid framework for predicting full-field temperature history that combines experimental temperature data with physical laws was developed for the first time by Liao *et al*.[14] The PINN model developed by them is depicted in Figure5. Furthermore, they conducted DED experiments and utilized FEM simulation results in their study to compare them with the predictions of the PINN model, thus demonstrating the effectiveness and accuracy of the model. Simultaneously, they also demonstrated that this hybrid framework could be employed for discovering unknown materials and process parameters. Peng *et al*.[23]and Sajadi *et al*.[24] mainly used the self-supervised learning ability of PINN to predict the two-dimensional temperature field distribution in the process of MAM.

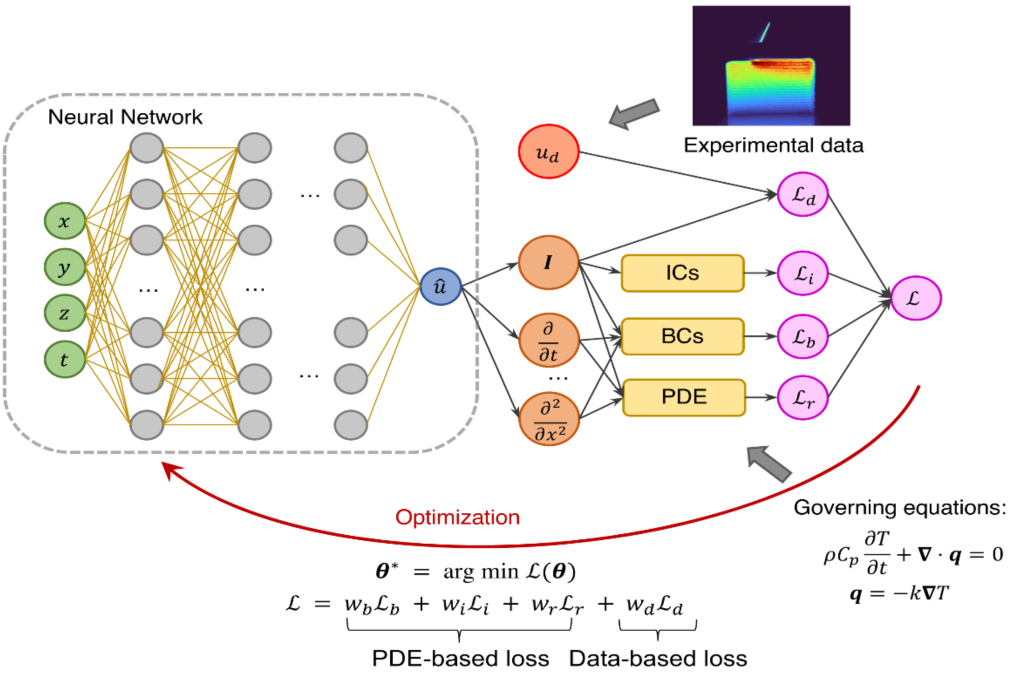

Figure 5. Hybrid thermal modeling framework for AM based on PINNs[14].

The process of laser additive experiments is complex. The cost of experimental equipment is high, and the accuracy of the sensor for data acquisition is also high. Consequently, generating labeled training data requires a significant investment of time and resources, resulting in increased experiment complexity, and cannot guarantee the quantity and quality of the data. Faced with this challenge, Hosseini *et al*.[25] employed unsupervised learning to train a PINN model is an example of calculating the transient and steady-state temperature profiles and molten pool dimensions during single-track LPBF deposition for any given process parameters and material thermal properties. This approach allows for calculations to be performed at nearly zero computational cost. This model considered the characteristics of the thermal process, and utilized eight parameters as input, including space-time coordinates, laser power, and absorption rate, to predict the temperature. Unlike the study by Liao *et al*. [14], only utilizing spatiotemporal coordinates as input, this method employed multiple parameters, thereby better constraining physical processes and improving the accuracy of model predictions. Similarly, even in the absence of any labeled data, the PINN model can be used to predict the 3D temperature field in the LMD process. This method was indicated in a study by Li and Wang[16]. Comparing the 3D temperature field and error distribution plots of PINN and FEM results, with three different time step settings, as depicted in Figure6, demonstrated that the PINN model's overall average error is lower than that of Xie *et al*.[26], who utilized the labeled training dataset. This PINN model remains applicable even when the material parameters are changed. Overall, the PINN model provides a novel approach for predicting the temperature field of thermally conductive materials during the AM process using this unsupervised learning method. Especially in the absence of experimental conditions and the difficulty of obtaining experimental data, this method leverages prior knowledge of physical laws to guide model learning, thereby achieving accurate predictions of complex thermal processes.

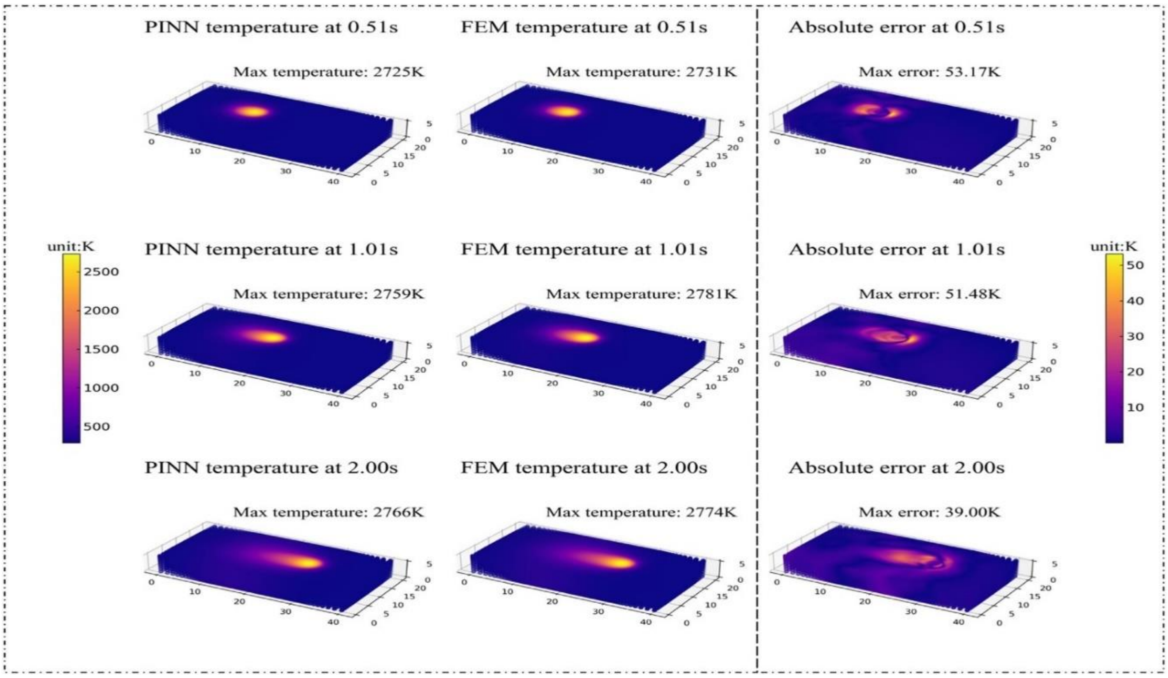

Figure 6. 3D temperature field and error distribution of PINN and FEM results in the deposition stage[16].

To predict the thermal conduction behavior during additive manufacturing processes, it is essential not only to consider the heat conduction partial differential equations but also to satisfy complex and specific boundary conditions to ensure the accuracy of predictions. When confronted with complex thermal transfer challenges characterized by specific boundary conditions and unknown coefficients, the PINN model emerges as a pioneering computational tool. The PINN model enhances prediction accuracy and reliability by embedding complex boundary conditions, such as convective heat transfer boundary conditions, into the loss function, thereby aligning the model more closely with physical laws. Conversely, traditional machine learning models typically overlook these boundary conditions, leading to inaccurate prediction results. Furthermore, the boundary conditions that need to be considered may vary in different scenarios, adding to the complexity of predictions. Navid and Keith [27] developed a PINN model specifically designed to address problems involving convective BCs and the PDEs of heat conduction when the convective coefficient is unknown. They ensured that the model learned all loss terms evenly during training by implementing an adaptive normalization scheme. This includes initializing weights and biases using the Glorot uniform initializer from Keras at the beginning of training, setting the factor values based on the ratio of each loss term to the maximum loss term, equal to 1 or adjusted proportionally, and periodically updating the normalization factors. Additionally, their research also found that the use of activation functions based on physical information is crucial for the model to accurately predict heat transfer phenomena outside the training domain. This contributes to the PINN model's ability to comprehensively predict temperature field distributions. Unlike utilizing fully connected neural networks as the foundational model for PINN, successfully embedding physical knowledge into neural networks, a model combining recurrent neural networks and deep neural networks employed by K. Ren *et al*. [28] for thermal field prediction in laser-assisted additive manufacturing (LAAM). This model utilizes training data generated by the FEM model and, through a unique data structure design, accurately predicts the thermal history distribution under different laser scanning strategies. This groundbreaking work significantly improves the efficiency and accuracy of thermal field prediction. The PINN model demonstrates its efficacy in temperature prediction by tackling intricate physical problems and boundary conditions. Through the incorporation of physical constraints into neural network training, it presents an innovative method for tackling complex heat conduction issues in practical engineering, yielding more precise temperature predictions. Nevertheless, despite notable advancements, challenges and areas necessitating improvement persist. Through further enhancing the model's interpretability, training efficiency, stability, and generalization ability, its accuracy in temperature prediction and solving complex heat conduction problems can be enhanced, thereby unlocking its potential and facilitating its application in engineering practice.

3.2. Fluid dynamics issues

In the field of fluid flow prediction, in scenarios of data scarcity, to overcome reliance on a large amount of labeled data and to simultaneously predict the melt pool temperature field while studying melt pool fluid dynamics, Zhu and Liu [29] proposed a PINN framework that integrates limited labeled data and physical principles, including momentum (Navier-Stokes), mass, and energy conservation laws. This marks the first application of physics-informed deep learning to three-dimensional additive manufacturing modeling. The prediction results of the PINN model were compared with the FEM simulation results and the video frames based on the experiment, as depicted in Figure7, demonstrating the feasibility of the PINN model. This study also proposes a hard-type method based on the Heaviside function to handle Dirichlet boundary conditions. This approach not only accurately enforces the boundary conditions, but also accelerates the learning process. Enhancing the multiphase Navier-Stokes model to capture evaporation phenomena and incorporating additional PDEs, such as level set or volume fluid methods [30], into PINN to model the powder-scale metal additive manufacturing process remains to be explored [29]. When addressing complex fluid dynamics problems, it is often challenging to meet the conditions required for conducting actual experiments. The experiments may be affected by factors such as high costs, equipment limitations, and poor data collection quality. Therefore, we need to find a model that combines the physical knowledge in fluid dynamics to replace traditional machine learning models that rely heavily on extensive experimental data. Moreover, the model incorporates boundary conditions that satisfy experimental requirements. Through this model, we can accurately predict the behavior of fluid flow without experiments or only rely on a small amount of experimental data, thus providing an effective and efficient method for the study of complex fluid mechanics problems. Zhang *et al*. [31] proposed a novel hybrid-variable PINN method. The method transformed the Navier-Stokes equation governing equations and the continuity equation into continuous and constitutive formulations, embedded within the loss function, enabling the resolution of fluid dynamics (flow past a cylinder) problems without the need for any labeled data. Additionally, boundary conditions and penalty factors were embedded into the loss function, ensuring a well-defined problem formulation. This hybrid-variable PINN method not only provides accurate predictions of flow fields but also automatically satisfies the physical constraints of fluid dynamics, thereby enhancing the reliability and generalization ability of the model. Furthermore, the study demonstrated that through transfer learning methods, fluid problems with different Reynolds numbers can be handled at lower computational costs. Boundary layer flow theory is a classic problem in the thermal fluid's domain, involving the viscous effects and heat transfer within the thin layer of fluid near a solid surface. This phenomenon finds numerous applications in engineering and industrial processes. The research by Bararnia and Esmaeilpour [32] applies Physics-Informed Neural Networks (PINNs) to address the challenges posed by viscous and thermal boundary layer problems, encompassing equations such as the Blasius-Pohlhausen and Falkner-Skan equations, as well as natural convection phenomena. They investigate how the nonlinearity of these equations and unbounded boundary conditions affects the adjustment of network width and depth. This study significantly advances the utilization of PINNs in problems related to fluid mechanics and heat transfer, particularly in tackling scenarios with complex boundary conditions and nonlinear characteristics. The application of PINN models in the field of fluid dynamics [33] holds tremendous potential, especially in scenarios of data scarcity, where complex fluid dynamics problems can be effectively addressed by combining physical laws and deep learning models.

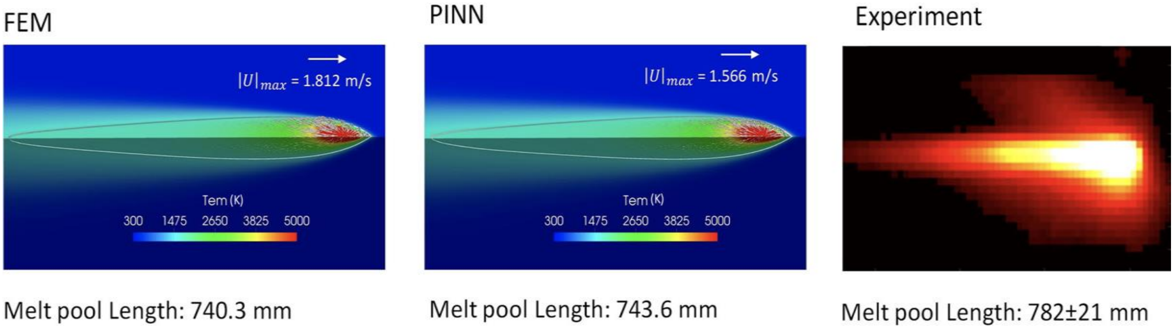

Figure 7. Comparison of the predictions of the temperature and melt pool fluid dynamics of FEM, PINN and experiment for case B (195 W, 0.8 m/s) at quasi-steady state (2 ms), when the melt pool shape is not changing [29].

3.3. Fatigue life prediction

Predicting the finite fatigue life of additively manufactured components ensures product quality and reliability, optimizes design, and prevents potential fatigue failures, thereby reducing costs and risks. The PINN model is capable of utilizing known physical laws to guide predictions, facilitating more accurate modeling outcomes. For predicting fatigue life, PINN models can leverage material mechanical properties and fatigue damage mechanisms, among other physical knowledge, to enhance prediction accuracy. A new PINN method, based on the neural network framework of the traditional concept of fracture mechanics employed by Enrico *et al*. [34] to predict the finite fatigue life of additive manufacturing metal materials, considered the morphological characteristics of porosity in the material, as depicted in Figure8. This PINN model integrated a new semi-empirical model from linear elastic fracture mechanics, as developed by Enrico *et al*. [34], and utilized the physical information component of PINN to improve the neural network training process. This integration enabled the model to capture the underlying physical laws of the problem more accurately, while also considering the morphological characteristics of defects in the material, which may not have been fully addressed when using the traditional LEFM model. Jiang *et al*. [35] proposed a novel multi-layer nested neural network framework that integrates physical constraints into neural networks to predict the low-cycle fatigue life of 316 stainless steel under different temperatures and strain rates. This approach significantly enhances computational efficiency and reduces resource consumption in predicting material fatigue life while maintaining adherence to physical principles.

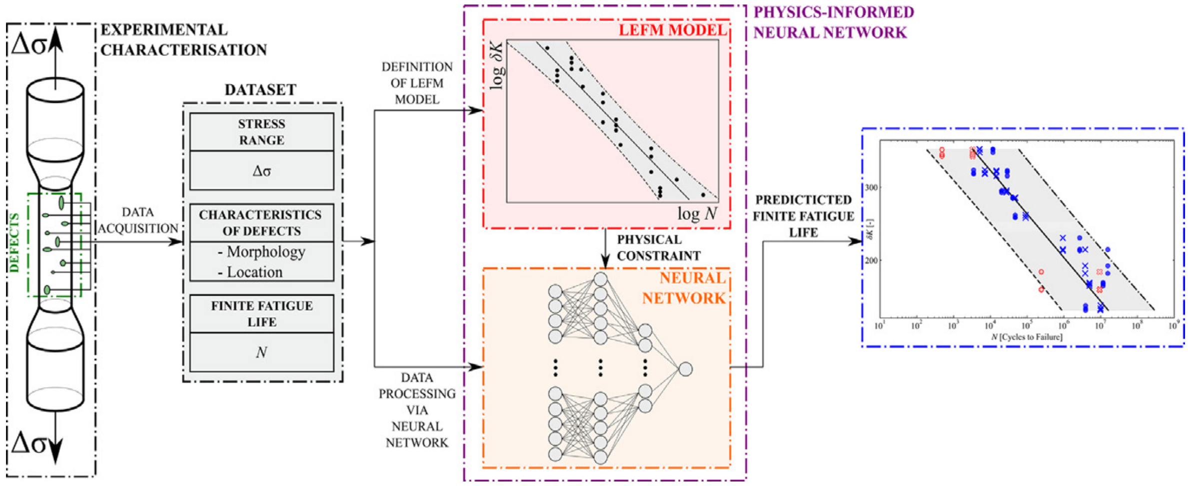

Figure 8. Structure diagram for fatigue finite life prediction of AM [34].

The defect characteristics are crucial to the fatigue life of additively manufactured components [36]. In the complex process of AM, various defects such as voids, pores, and cracks may inevitably occur. These defects not only compromise the integrity of the components but also lead to stress concentration and crack propagation under loading, significantly affecting the durability and safety of the components. Therefore, when predicting the fatigue life of components, it is essential to fully consider the influence of these defect characteristics on their performance [37]. In this context, the PINN framework emerges as an innovative solution of particular significance. By incorporating the association between defect characteristics and fatigue performance into the training process of neural networks, the PINN framework can more accurately simulate the fatigue behavior of components under various defect conditions. In the complex process of additive manufacturing, it is difficult to avoid various defects. To accurately assess these geometric morphology defect characteristics, such as defect size, shape, location, and area as well as their impacts on fatigue performance, Wang and Zhu [38] proposed a novel defect-driven PINN framework, which guides the training process of the network by incorporating the influence of defect characteristics on fatigue performance as prior knowledge. Predicting fatigue life is crucial for ensuring the stability, safety, and reliability of products throughout their entire service life. Embedding key defect information into the loss function can enhance the accuracy of the model in predicting fatigue life. This PINN framework has the potential to further quantify the effects of additional defect characteristics, residual stresses, and microstructures on the fatigue performance of AM materials. Ciampaglia *et al*. [39] employed a Physics-Informed Neural Network (PINN) model, integrating knowledge of physical processes, notably accounting for the influence of manufacturing defects such as voids or fusion defects, to assess the fatigue life of AlSi10Mg alloy components manufactured via Selective Laser Melting (AM). The PINN model not only learned the complex mapping relationship from manufacturing parameters to fatigue strength, but also considered the specific effects of these defects and the microstructure of the material on fatigue life. This study demonstrates the effectiveness of the PINN model in predicting finite fatigue life.

3.4. Accelerated finite element simulation

Finite element simulation [40] plays a crucial role in additive manufacturing by predicting and optimizing component designs, simulating thermal conduction and solidification processes, and predicting defects and fatigue life, thereby enhancing component quality, reducing manufacturing costs, and saving time. However, traditional finite element simulation often exhibits low computational efficiency when tackling complex problems. The PINN model can leverage the advantages of combining physical principles or coupling with finite element models to accelerate the finite element simulation process, providing a more efficient solution for AM. The research conducted by Virama and André [41] explores the application of PINN in accelerating finite element simulation (FE-simulation), particularly in the context of modeling additive manufacturing processes involving materials exhibiting time-dependent properties. They elaborated on the training process of PINN and implemented a network architecture with three hidden layers. The study successfully demonstrated that PINN can replace numerical iterations in the additive manufacturing process, thus accelerating finite element simulation. As shown in Figure 9, the convergence of PINN and the accuracy of determining the plastic multiplier $\Delta\gamma$ were illustrated by comparison with numerical iterations. Through the application of PINN, faster material behavior simulation and analysis can be achieved in additive manufacturing, which is crucial for optimizing the printing process and material selection. Zhou [42] *et al*. innovatively couple the PINN and Smoothed Finite Element Method (S-FEM) methods, proposing a novel computational framework aimed at enhancing the computational accuracy of solving PDEs, as shown in Figure10. This coupling method can overcome the limitations of individual methods, such as the low computational efficiency encountered by traditional finite element simulation methods when dealing with certain complex problems. This study offers a novel perspective and approach for the application of PINN in accelerating and enhancing finite element simulation model solutions for PDEs. PINN not only accelerates the simulation process but also handles incomplete or noisy data. Zhou and Mei [43] proposed a coupling method of S-FEM based on transfer learning with PINN to enhance the accuracy and efficiency of parameter inversion. Especially in cases where data is limited. This approach utilizes S-FEM to generate high-quality small datasets, combines them with PINN for pre-training, and then employs transfer learning techniques to accelerate the model training process for new datasets. This study effectively demonstrates the advantages of integrating physical information and transfer learning into the PINN model, showcasing its potential application in accelerating finite element simulation.

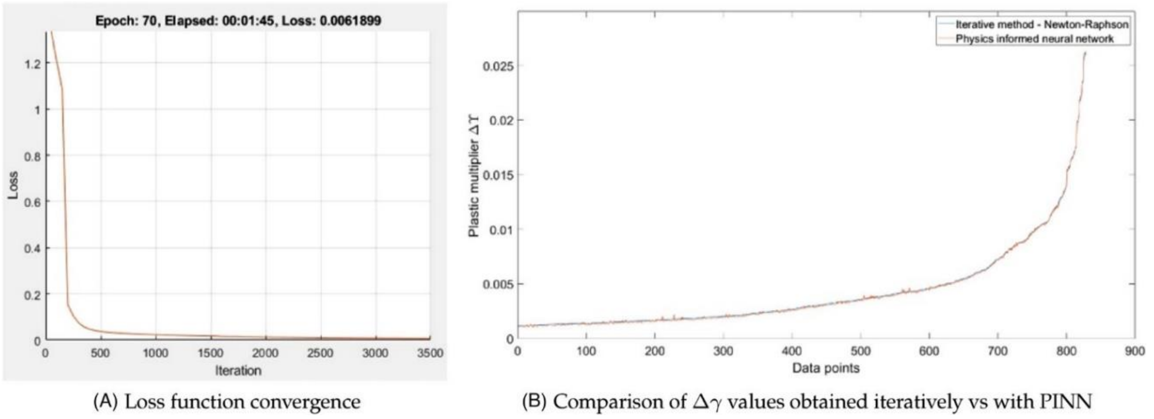

Figure 9. Convergence and performance of PINN. (A) Loss function convergence. (B) Comparison of $\Delta\gamma$ values obtained iteratively versus with PINN [41].

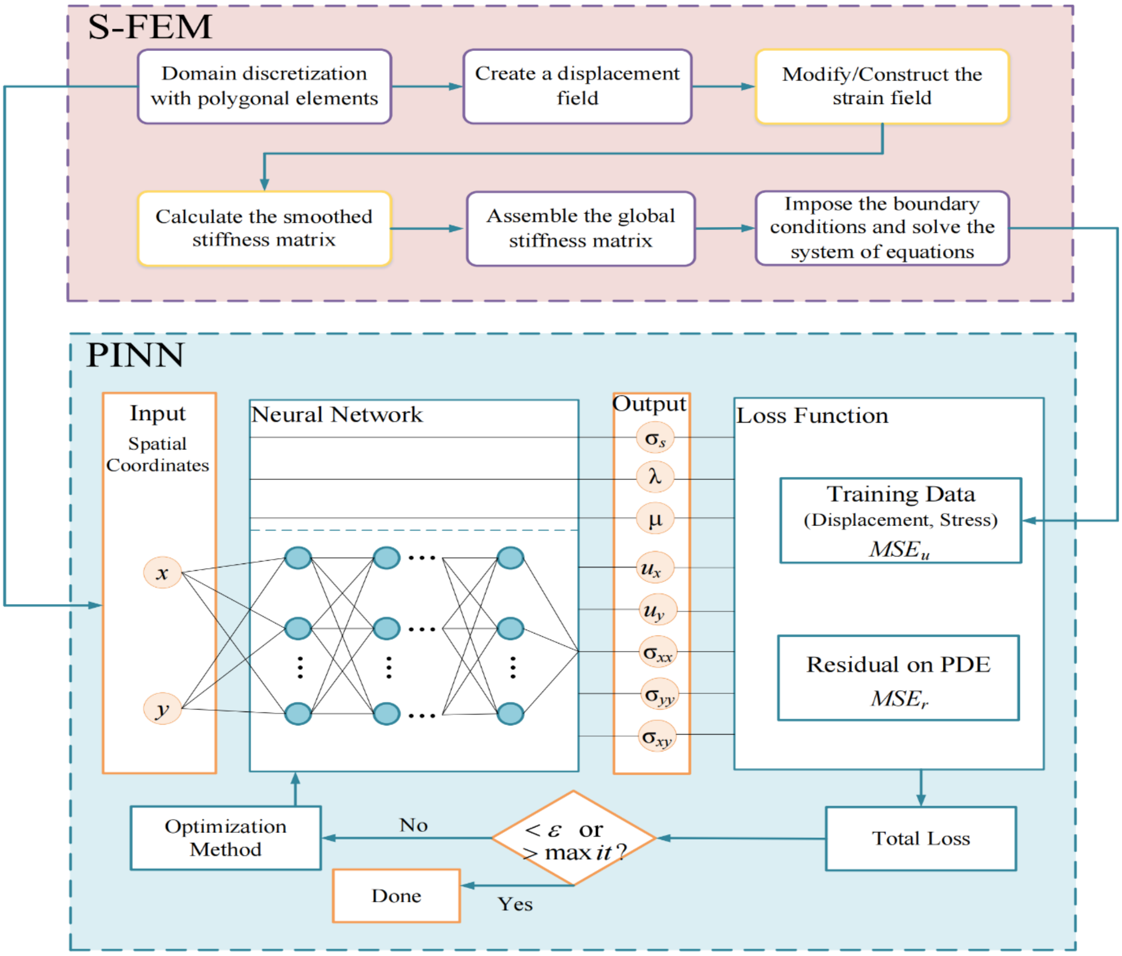

Figure 10. Illustration of the S-FEM-coupled PINN for solving the two-dimensional static elastic–plastic inverse problem [42].

3.5. Process characteristics prediction

The process characteristics of the melt pool are crucial for predicting defects in the additive manufacturing process. Traditional machine learning methods typically utilize high-speed cameras to capture images of the melt pool, to predict its process characteristics [44]. However, this approach [45] not only requires extensive data collection through experiments but also often yields limited accuracy. In contrast, the PINN model can accurately predict the process characteristics of the melt pool, including its size and porosity, by integrating physical principles with a small amount of labeled data. Jiang *et al*. [46] proposed a PIML model incorporating partial differential equations into neural networks, enabling accurate prediction of the temperature distribution and melt pool size in the metal AM process. Furthermore, the prediction model can handle different scanning speeds, rather than only a specific scanning speed in previous studies. This approach saved time required for training multiple models, while also possessing broader applicability. Kapusuzoglu *et al*. [47] proposed three novel fusion strategies to integrate physical principles into deep learning models to enhance the prediction accuracy of part bonding quality and porosity rates. These strategies involve integrating physical constraints into the loss function, utilizing the output of a physics model as additional input to the deep neural network (DNN) model, and updating the model with experimental data. The study also improved the physics model by considering the geometric shape of the filament material and its variations during the printing process. The combined application of these strategies offers a more effective approach to defect prediction in additive manufacturing, thus promoting the widespread utilization of the PINN model in this field. Wenzel *et al*. [48] proposes a new methodological framework by integrating machine learning and physical models to enhance the system reliability in additive manufacturing processes. And introduced a new approach by employing neural networks to predict system responses and optimizing algorithms tailored to specific system boundary conditions to achieve reliability enhancement. Through the methods proposed in this study, enabled more precise adjustment of printing parameters, reduced printing defects, improved product quality, and ultimately achieved more efficient industrial production.

4. Challenges and outlook of PINN

In AM fields, there is a current shift occurring from traditional data-driven and purely physics-based models to the PINN model. The PINN model is widely applied in additive manufacturing due to its advantage of integrating physical information. Yet, the PINN model still has some unresolved shortcomings at present. This section explores the challenges faced by the PINN model and outlines future research directions.

4.1. Data availability and preprocessing

In the field of AM, although the PINN model can reduce reliance on a large amount of labeled data, some experimental data is still necessary to verify the consistency of the model. As demonstrated by the research conducted by Liao *et al*. [14], the addition of auxiliary data can enhance the accuracy and convergence speed of the PINN model when solving forward problems. Furthermore, compared to training without auxiliary data, the incorporation of auxiliary data allows for achieving similar accuracy levels in only one-third of the iterations. Therefore, for certain specific problems, the utilization of a small amount of labeled data is necessary to enhance the predictive accuracy of the model. Additionally, the data input into the PINN model usually requires preprocessing steps including data cleaning, selecting features closely related to physical problems, and data normalization. The purpose of preprocessing is to ensure the quality of input data, align it with the physical problem being solved, and maximize the effectiveness of model learning. For example, when predicting the three-dimensional temperature distribution, it is necessary to process temperature image data collected by infrared cameras to obtain the spatiotemporal coordinate dataset inputted into the PINN model. Labeled data needs to represent the entire problem space to ensure the model has good generalization ability, posing challenges in acquiring complex experimental data.

4.2. High training cost and poor scalability

PINNs are commonly employed to solve complex nonlinear PDEs that may involve multiple variables and intricate boundary conditions. Additionally, the training process of PINNs requires not only fitting data but also satisfying physical laws [49], namely the constraints of PDEs. This implies that the network must simultaneously learn patterns from the data and satisfy the equations' solutions. This dual learning task increases the complexity of the training process. Therefore, during the training process, PINNs may require a lot of computing resources and time, which limits the use of models in real-time applications in AM. When PINNs are applied to problems in large-scale or high-dimensional spaces, the required computational resources (such as memory and processing power) may increase significantly. In high-dimensional spaces, PINNs need to be able to capture and learn the complex patterns present in the data. As the dimension increases, the model may require more layers and neurons to represent these patterns, increasing the complexity of the model and potentially leading to overfitting. Therefore, PINNs face scalability challenges when dealing with large-scale or high-dimensional space problems, which may result in a complex, unstable, and inefficient training process.

4.3. Choice of differential equations

In the fields of science and engineering, the accurate selection of PDEs is a crucial step in constructing PINN models and addressing problems. The process of selecting PDEs requires an in-depth understanding of the physical principles behind the problem, considering the applicability of the equation in specific situations and the feasibility of mathematical solutions. It is necessary to comprehensively use the interdisciplinary knowledge of physics, mathematics, and engineering, as well as modern computing technology and data analysis methods, to ensure that the selected equations can effectively capture the core characteristics of the problem and provide accurate predictions in practical applications. Understanding the physical principles underlying the problem is crucial, implying the comprehension of the fundamental operating principles of the model, boundary conditions, and other pertinent factors. For instance, in fluid dynamics problems, it is essential to consider factors such as the dynamics of fluid motion, and interactions between fluid and solid interfaces, to select appropriate and accurate PDEs. Additionally, the choice of solution methods for the PDEs must also consider the complexity of the problem and the constraints of computational resources.

4.4. Outlook of PINN

Overall, PINN models face challenges in terms of difficult data acquisition, high training costs, poor scalability, and difficulties in selecting physical differential equations. These challenges need to be overcome in future research efforts. Enhancing the performance of neural networks, optimizing network architecture, and developing more efficient neural network structures can reduce the required training time and resources This includes improving the depth and width of networks, as well as exploring novel activation functions that are more suitable for specific types of PDE problems. Pu and Li *et al*. [50] proposed an improved PINN method based on neuron-based local adaptive activation functions, aimed at solving local wave solutions of nonlinear partial differential equations in complex spaces, thereby enhancing the performance of neural networks. To enhance the scalability of the model, new parallel computing strategies and distributed training methods can be developed, enabling the model to better address large-scale and multi-physics coupling problems. New data acquisition and enhancement techniques can be developed to obtain high-quality training data. Physics-based knowledge can be utilized to generate synthetic data, alternatively, transfer learning and meta-learning can be employed to pre-train models on relevant tasks, thus enhancing data efficiency [49].

Facing the challenging task of selecting physical PDEs, the knowledge and experience of domain experts can be used to guide the selection of equations. Experts' understanding of specific physical phenomena can assist in determining the most suitable PDEs to describe those phenomena. Developing and applying machine learning algorithms to automatically learn physical models from experimental data. Analyzing patterns and relationships in data to extract physical knowledge from observational data [51], using artificial intelligence to explore physical principles automatically, can be termed as machine learning-based discovery of physics knowledge. This approach can reduce reliance on human intuition and may uncover new, unknown physical laws. Additionally, employing deep learning-based data-driven methods [52] can aid in discovering and validating partial differential equations, facilitating the selection of appropriate equations based on model performance.

5. Conclusion

This paper describes the pros and cons of the traditional data-driven and pure physical models in AM applications, such as relying on a heavy reliance on extensive labeled data and lacking physical laws. Subsequently, the advantages of the PINN model in additive manufacturing applications are introduced. Compared with the data-driven method, the PINN model overcomes the reliance on extensive labeled data, ensuring the model's adherence to physical laws and enhancing prediction accuracy. Compared with the traditional pure physical model, the PINN model overcomes limitations in handling complex systems and incomplete data, offering a more flexible, efficient, and accurate approach to modeling and prediction. As detailed in Section 2, the paper elaborates on the fundamental principles, research strategies, and underlying architecture of the PINN model, including the selection of the foundational neural network model. Additionally, examples are provided to illustrate how partial differential equations and boundary conditions are embedded into the loss function.

We elaborate on the relevant research of the PINN model in the field of additive manufacturing, specifically, temperature prediction, fluid dynamics issues, fatigue life prediction, accelerated finite element simulation, and process characteristics prediction. Combining thermal conduction differential equations, it is possible to predict three-dimensional temperature distributions even when labeled data is scarce or auxiliary data is unavailable. The PINN model holds tremendous potential in the field of fluid dynamics, as it can integrate principles of energy conservation, mass conservation, momentum conservation laws, and the Navier-Stokes equation to predict fluid flow more accurately. The PINN model can also be employed to predict the fatigue life during additive manufacturing processes. In this scenario, it is capable of integrating the physical properties based on defects, thereby enhancing the accuracy of fatigue life prediction. The finite element simulation is a powerful tool for analyzing the AM process, and the PINN model also helps to accelerate this simulation. Additionally, process characteristics are one of the key indicators for assessing defects, and the PINN model, by integrating physical knowledge, can accurately predict critical process features such as melt pool shape, porosity, and printing defects. The application of this model not only contributes to improving the accuracy of defect detection during the production process but also provides crucial references for optimizing process parameters.

PINN model still faces several challenges, such as the difficulty in obtaining a small amount of labeled data, high requirements for data quality, high training costs, poor scalability, and the challenge of selecting appropriate physical partial differential equations. Developing more efficient neural network architectures in the future is expected to reduce training time and resource costs. Follow-up studies utilizing new parallel computing strategies and distributed training methods can enable the model to better address large-scale and multi-physics coupling problems. Developing new data acquisition and enhancement techniques or leveraging physics-based knowledge to generate synthetic data, can yield high-quality training data. The knowledge and experience of domain experts guide the selection of equations. Machine learning-based methods are employed to discover physical partial differential equations from observed data, and data-driven methods based on deep learning are utilized to assist in the discovery and verification of these equations. These methods address the challenge of selecting appropriate physical PDEs. In future work, it is imperative to address the limitations of the PINN model, enhance its robustness, and thereby foster its increasingly widespread adoption and popularity in AM and related fields.

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Conflicts of interest

The authors declare no conflict of interest.

Authors' contribution

Shoulan Yang: Conceptualization, Writing - original draft, Software. Shitong Peng: Supervision, Writing - review & editing, Funding acquisition. Jianan Guo: Methodology, Funding acquisition. Fengtao Wang: Funding acquisition.

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