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The application of artificial intelligence in mechanical simulation

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Abstract:

As computing capabilities surge forward and artificial intelligence progresses significantly, the integration of AI into mechanical simulation is expanding at a notable rate, substantially boosting advancements in engineering and scientific investigation realms. This article mainly explores three types of applications of artificial intelligence in mechanical simulation: surrogate models, physics-informed neural networks (PINNs), and adaptive grid refinement. These technologies improve the efficiency and accuracy of simulation and open up new research directions and application areas. In summary, the application of artificial intelligence technology in mechanical simulation has made significant progress. Still, it faces challenges such as strong data dependence, limited model generalization ability, and optimization of computational efficiency. Future research needs to conduct in-depth exploration into improving algorithm efficiency, enhancing model generalization ability, and expanding application scenarios. In addition, strengthening the combination of theoretical research and practical application will be an important direction for promoting the sustainable development of this field.

Keywords: artificial intelligence; mechanical simulation; solid mechanics; PINN

1. Introduction

Engineering simulation plays an important role in engineering design and manufacturing, which can accelerate the iteration of design, assist the optimization of the structure, and ensure the safety of the structure in the use process. The primary role of AI in engineering simulation is to speed up complex calculations. There are many nonlinear problems in simulation calculation, such as material nonlinearity, geometric nonlinearity, large deformation, and other complex problems, using traditional simulation technology, which requires many calculations and cannot achieve real-time solutions and predictions. In genuine manipulation and instantaneous handling, it is imperative to swiftly anticipate the distortion and determine the necessary adjustments for precise manipulation. Utilizing AI frameworks facilitates rapid computations to fulfill the necessary criteria. Currently, there is a growing focus on the use of substitute models that feature straightforward input-output pairs for the training dataset, while concurrently, the machine learning approach that incorporates the underlying physical principles is gaining more recognition,

with the PINN network successfully addressing partial differential equations. In this article, the current research work is sorted out and classified, and the current development status, difficulties, and possible future development directions are pointed out.

2. The foundation of artificial intelligence

A neural network (NN) is a complex network system that is widely connected by a large number of simple processing units (called neurons). It reflects many basic characteristics of human brain function and is a highly complex, non-linear, dynamic learning system. The neural network has large-scale parallelism, distributed storage and processing, self-organization, adaptation, and self-learning ability, so it is particularly suitable for the problem of inaccurate and blurred information processing. Many factors and conditions need to be considered at the same time.

2.1 Basic principle

The fundamental framework of the artificial neural network is depicted in Illustration 1. This framework comprises input nodes, output nodes, and intermediate nodes. Input nodes gather information and stimuli from the external environment; output nodes deliver the processed outcomes of the system; intermediate nodes, positioned between input and output nodes, are not directly observable from the system's exterior. The synaptic weights linking neurons denote the intensity of the interconnections among nodes, with the depiction and manipulation of information being manifested through the interconnectivity patterns among the network's processing nodes.

The neural network passes the input data layer by layer and calculates the output layer by layer. Taking a single-layer neural network as an example, the basic formula is as follows:

$$a^{(l+1)} = \sigma\left(W^{(l)}a^{(l)} + b^{(l)}\right) \tag{1}$$

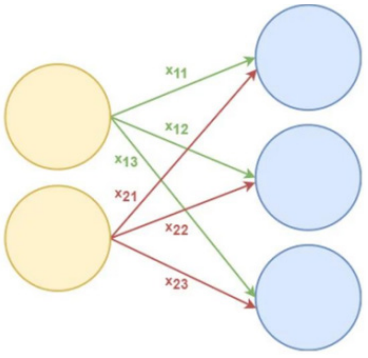

Fig1 Sketch map of neural network

Where $a^{n(l)}$ is the activation value of the n-th layer, $W^{(l)}$ is the weight matrix of the n-th layer, $b^{(l)}$ is the bias vector of the n-th layer, σ is the activation function.

Where common activation functions include:

$$Sigmoid : \sigma(x) = \frac{1}{1+e^{-x}} \tag{2}$$

$$ReLU : \sigma(x) = max(0, x) \tag{3}$$

The objective function employed for assessing the discrepancy between the neural network's estimated output and its actual target value is referred to as the loss function. Prominent among these is the Average squared deviation (Quadratic Loss, QL).

$$L(\grave{y}, y) = \frac{1}{n}\sum_{i=1}^{n} ?\left(\grave{y}_i - y_i\right)^2 \tag{4}$$

Where $\grave{y}_i$ is the predicted value, y_i is the true value, n is the number of samples.

Backpropagation was used to calculate the loss function gradient relative to the weight and bias. Taking the mean square error as an example, the gradient is calculated as follows:

$$\frac{\partial L}{\partial W^{(l)}} = \delta^{(l+1)} \cdot \left(a^{(l)}\right)^T \tag{5}$$

$$\frac{\partial L}{\partial b^{(l)}} = \delta^{(l+1)} \tag{6}$$

where $\delta^{(l+1)}$ is the error terms of the $l+1$ th layer.

Gradient descent is used to update the weights and bias of the neural network:

$$W^{(l)} := W^{(l)} - \alpha\frac{\partial L}{\partial W^{(l)}} \tag{7}$$

$$b^{(l)} := b^{(l)} - \alpha\frac{\partial L}{\partial b^{(l)}} \tag{8}$$

Where α is the learning rate.Hidden state update formula:

$$h_t = f(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \tag{9}$$

h_t Is the hidden state of the time-step t, tx Is the input to the time-step t, $andW_{xh}$ Is the weight matrix of the input to the hidden layer. W_{hh} Is the weight matrix of the hidden layer to the hidden layer. b_h Is the bias of the hidden layer. And f is an activation function. A dOutput formula:

$$y_t = g(W_{hy}h_t + b_y) \tag{10}$$

· y_t Is the output of the time-step t.

· W_{hy} Is the weight matrix of the hidden layer to the output layer.

· $_{By}$ Is the bias of the output layer.

· The g is the activation function of the output layer (usu-

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ally a softmax or a linear activation function, depending on the specific task).

2.2 Basic classification

A neural network is a computational model that mimics the nervous system of a living organism and consists of many interconnected neurons (nodes). Depending on their structure and function, neural networks can be divided into the following main types:

1) Fully Connected Neural Network (FCNN): The most basic neural network structure, suitable for processing static data with no spatial or temporal dependence. FCNN excels in predicting stress-strain relationships and other mechanical properties of materials. The basic equation is shown in Eq.(1).

2) Convolutional Neural Network (CNN): Mainly used to process data with spatial structure, such as images. CNNs extract local features from data through convolution operations and fuse information at multiple levels, making them ideal for material analysis that includes images of microstructures.

3) Recurrent Neural Network (RNN): Good at processing time series data or dynamic data with path dependence. RNNs are able to capture the time dependence of data through feedback connections, which is advantageous in cyclic loading and fatigue analysis of materials.

2.3 Introduction to the Physical Information Neural Network

After discussing Fully Connected Neural Networks (FCNN) and their diverse applications in the field of machine learning, we will delve into an interesting variant of neural networks: Physically Integrated Neural Networks (PINN). Physics-Incorporated Neural Networks (PINN) require a technique that integrates physical principles into a neural network framework. In traditional neural network architectures, the loss function is usually constructed based on the difference between the stress or strain predicted by the model and the actual results obtained by experiments or simulations. The loss function contained in PINN is more than just the data fitting error; it also contains a variety of physically consistent constraints or equations, including principles such as conservation of mass and the laws of thermodynamics. By doing so, PINN not only conforms to the data but also keeps the model consistent with physical principles, thereby improving the model's predictive accuracy and reliability. In Physical Information Neural Networks (PINN), the loss function aims to integrate data fitting errors and physical rules. Here is the basic formula for PINN:

Loss function:

$$L = L_{data} + L_{physics} \tag{11}$$

L_{data} is the error of data fitting, and $L_{physics}$ is the error of physical constraint.

For example, the error of data fitting can be the mean square error:

$$L_{data} = \frac{1}{n}\sum_{i=1}^{n} ?\left(\grave{y}_i - y_i \right)^2 \tag{12}$$

The error of the physical constraint can be the residual difference of the partial differential equation (PDE):

$$L_{physics} = \frac{1}{m}\sum_{j=1}^{m} ?\left(\frac{\partial u}{\partial t} + \mathcal{N}[u] - f \right)^2 \tag{13}$$

In the equation, $\mathcal{N}[u]$ is the operator describing the physical phenomenon, f is the external force or source term, and u is the physical quantity to be solved.

3. Research progress of AI in engineering simulation and calculation acceleration

Conventional finite element method (FEM) or calculation of fluid dynamics (CFD) computing is often highly calculated,which shows great importance. By merging artificial intelligence, especially the physical model driven by neural networks, the duration of these calculations can be significantly reduced. Use the application of machine learning algorithms to quickly predict structural behavior under pressure conditions.

3.1 Surrogate Models

Agent models represent a transformative approach in the fields of computational engineering and physics, providing an efficient alternative to traditional simulation methods that often require extensive computational resources and time. These models leverage advanced machine learning techniques to simplify mathematical expressions of complex physical phenomena, making rapid prediction and analysis possible while maintaining high accuracy.

Surrogate models are an alternative to traditional simulation methods that can significantly reduce computational time while maintaining simulation accuracy. Common agent models include those based on neural networks, support vector machines (SVM), Gaussian Processes, etc. By training these models, complex physical phenomena can be approximated with simpler mathematical expressions, allowing for rapid prediction. Jang et al. [1] used an artificial neural network (ANN) instead of the traditional nonlinear stress integration approach, achieving both greater accuracy and computational efficiency. Hashemi and colleagues [2] created machine learning-based replacement

methodologies tailored for finite element analysis (FEA) in the context of dynamic mechanical system behavior, which can reliably predict the behavior of a lattice structure in The research team led by Barmada [3] introduced and implemented an advanced deep learning substitute approach for topology optimization, significantly cutting down the time required for computation. Xu and colleagues [4] introduced an innovative technique for forecasting the mechanical characteristics of biphasic composites through transfer learning, matching the accuracy of the standard CNN approach while utilizing only half of the data. Weng and associates [5] established a connection between the fabric tensor and the anisotropic cyclic plastic behavior of nickel-based single-crystal alloys using artificial neural networks. The neural network confirms that the fabric tensor can present an anisotropic single-crystal microstructure and describe the corresponding mechanical behavior. The efficiency of the agent model method based on artificial intelligence has been improved, but it lacks physical mechanisms and is difficult to apply in practical engineering.

3.2 Physics-Informed Neural Networks

PINNs embed physical laws (such as partial differential equations) directly into the loss function of neural networks, enabling the model to not only learn through data but also follow physical constraints. This approach is able to effectively learn complex physical phenomena in the absence of large amounts of high-quality data and significantly accelerate simulation. For anisotropic elastoplastic responses, Heider et al. [4] proposed an informed-graph-based neural network (see Figure 2) and studied the effect of the way to represent tensors.

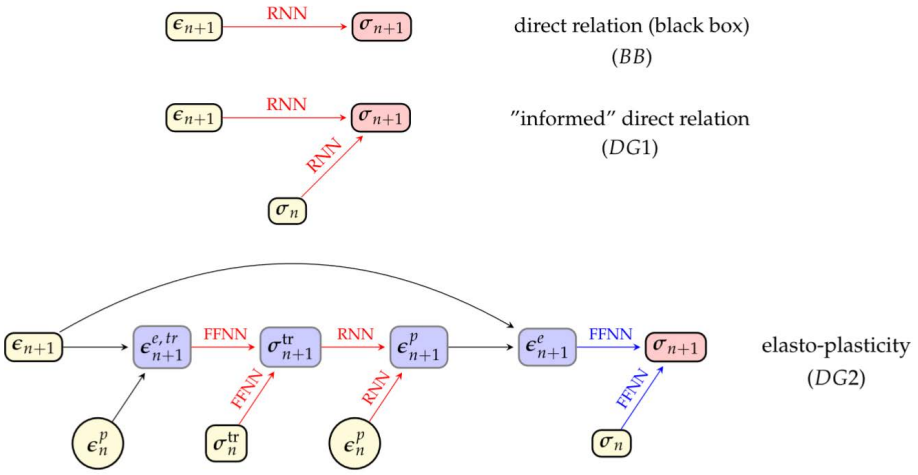

Fig2. Sketch map of informed-graph-based neural networks.

In the studies conducted by Raissi and colleagues [1], Schiassi and team [21], as well as Zhang and associates [22], it has been highlighted that the primary drawback of conventional PINs lies in the fact that the mathematical resolution of DE constraints remains unresolved. Consequently, these constraints must be acquired concurrently with the DE solutions within the domain. Schiassi has introduced an innovative technique, denoted as E, which is capable of being utilized in data-driven explorations and resolutions for parametric differential equations. Ongoing scholarly endeavors are geared towards expanding the application of this technique to the identification of data-driven problems, specifically targeting ODEs, through the utilization of both deterministic and probabilistic methodologies.

Chen's advanced PINN method, as championed by Pu J. and Lee J., has significantly bolstered the efficacy of neural network systems. They highlight that due to the multitude of trainable variables within the activation function, a pivotal challenge on the horizon is to explore the extensive application of machine learning principles, drawing from the integrable systems theory, to construct a vast array of integrable deep learning protocols.

3.3 Adaptive Grid Refinement (Adaptive et al.)

The adaptive grid refinement technology significantly improves simulation efficiency by dynamically adjusting the resolution of the computational grid during the simulation process. In recent years, artificial intelligence technology has been introduced into adaptive mesh refinement (AMR), which can intelligently predict which areas require higher resolution, making simulations more efficient. The application of this technology has shown great potential and advantages, especially in fields such as computational fluid dynamics. The study by Huang et al. [5] is a typical example, who used machine learning methods to determine the optimal mesh density for computational fluid dynamics needs. This method avoids complex calculation processes while providing high-quality meshes

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and effectively improves the automation and intelligence level of mesh generation. Through training machine learning models, the system can automatically adjust the grid density according to the characteristics of the flow field and dynamic changes, especially in the key areas of fluid flows, such as the boundary layer, wake up, and the vortex, ensure the accuracy of calculation and optimize the use of computing resources to use the use of computing resourcesEssenceThis intelligent grid improvement strategy not only improves the accuracy and efficiency of simulation but also reduces the demand for computing resources [6], thereby making the simulation of complex fluid dynamics more economical and efficient. In addition, the development of this technology has also promoted the transformation of traditional engineering simulation fields into digital and intelligent ones, providing new solutions for handling more complex engineering problems. In the future [7], with the further improvement of machine learning technology and computing in electric power, it is expected that adaptive grid refinement technology will be promoted in more engineering application fields, especially in situations where high computational accuracy and efficiency requirements are required. At the same time, this will also encourage more researchers and engineers to explore how to integrate artificial intelligence more deeply into simulation technology, opening up new horizons in simulation technology [8].

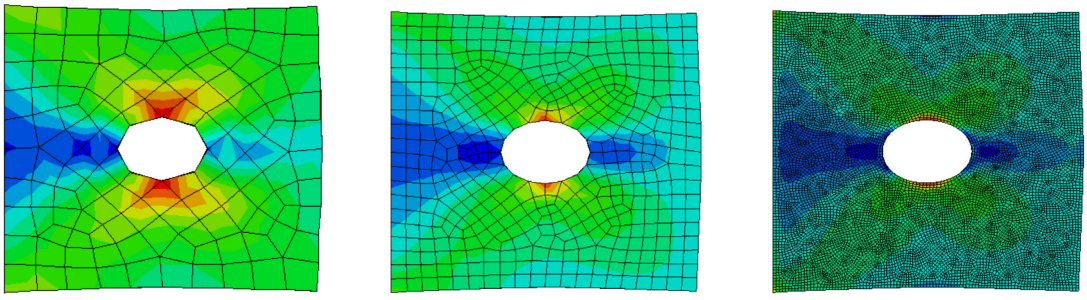

Fig 3. Adaptive grid refinement

4. Conclusion

In this article, we comprehensively explore three main applications of artificial intelligence in the field of mechanical simulation: surrogate models, physics-informed neural networks (PINNs), and adaptive grid refinement. These technologies each demonstrate how to improve the efficiency and accuracy of traditional simulations through intelligent methods. Although these advances are encouraging, challenges in applications, such as data dependencies, insufficient model transparency, and the complexity of algorithm implementation, still need to be overcome. Future research should focus on improving the data processing capabilities of these technologies, enhancing model interpretability, and exploring new methods that integrate various technological advantages to further promote the application of artificial intelligence in mechanical simulation and solve a wider range of engineering problems. In addition, strengthening interdisciplinary cooperation will also be an important driving force for promoting technological innovation and practical applications in this field.

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