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Applications of physics-informed neural networks in solid mechanics

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ABSTRACT

The applications of machine learning techniques and particularly deep learning frameworks have been extensively developed in the last decade in various fields such as image processing, handwriting and voice recognition, and computer vision. Taking the science and engineering aspects into account, deep learning techniques have been utilized in different research areas like material science [1], fluid and solid mechanics [2,3], and structural health monitoring [4]. The immensely complex nature and expensive data attainment in engineering systems make the employment of machine learning techniques difficult. On the other hand, a sufficiently large amount of data is needed to train deep neural networks which might not be available for engineering problems. This is where physics-informed neural networks (PINN) can efficiently come into play in which the governing equations related to the physics f the problem is employed along with the existing data to train the neural networks. Indeed, in addition to data commonly used in neural networks, the cost function includes the partial differential equations of the problem as well as the related boundary and initial conditions to perform the training of the PINN. Recently, the applications of PINN in mechanical engineering have been demonstrated in the literature [5,6]. A comprehensive review on the topic was presented in [7]. The main objective of this study is to investigate the performance of the PINN in learning and the solution of problems in solid mechanics like static 2D elasticity and thin-plate bending problems. The implementation of governing equations including the stress(resultants)-strain relations and equilibrium differential equations in PINN is briefly described and then the impacts of several architectural factors such as the number of hidden layers and neurons per layer, as well as algorithmic parameters like batch-size, number of epochs, learning rate, and the number of sample points are studied to highlight the performance of the proposed PINN. The results indicate the high importance of each factor so it is crucial to conduct the parametric study to find the best neural network architecture and algorithmic parameters.

Keywords: Deep learning, Physics-informed neural networks, Solid mechanics, 2D elasticity, Plate bending

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