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An Examination of Physics-based Machine Learning in Civil Engineering

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Abstract

The potential are expanding across all industries thanks to the recent advancements in machine learning (ML) and deep learning (DL). Although ML is a useful tool that may be used in many different fields, it can be difficult to directly apply it to civil engineering issues. Lab-simulated ML for civil engineering applications frequently fails in real-world assessments. This is typically linked to a phenomenon known as data shift, which occurs when the data used to train and test the ML model differ from the data it meets in the real world. To address data shift issues, a physics-based ML model integrates data, partial differential equations (PDEs), and mathematical models. In order to accomplish supervised learning problems while adhering to any given laws, physics-based ML models are trained. Physics-based Fluid dynamics, quantum physics, computational resources, and data storage are among the many scientific fields where machine learning (ML) is taking centre stage. This essay examines the development of physics-based machine learning and its use in civil engineering.

Keywords: Civil engineering; Machine learning; Physics

Introduction

Deep neural networks (DNNs), for example, are replacing conventional statistical techniques and mechanistic models in a variety of commercial applications and sectors, such as education, natural science medicine engineering and social science. In civil engineering, where mechanistic models have historically predominated, ML is also used. Despite their widespread use, ML approaches are frequently criticised by researchers and other end users as being "black boxes," which refers to the idea that they accept inputs, produce outputs, but do not give the user information that can be physically understood. As a result, several researchers have created physics-based machine learning (ML) to address the general worry of the opacity of black-box models. In civil engineering, where mechanistic models have historically predominated, ML is also used. Despite their widespread use, ML approaches are frequently criticised by researchers and other end users as being "black boxes," which refers to the idea that they accept inputs, produce outputs, but do not give the user information that can be physically understood. As a result, several researchers have created physics-based machine learning (ML) to address the general worry of the opacity of black-box models. [1, 2].

Materials and Method

Low-order models

For accurate results, the field of research known as computational mechanics requires a lot of processing power. It almost always employs a geometric mesh, and the time it takes for a simulation to converge is proportional to how coarse the mesh is. It could so expand to such size those strategies for decreasing its order need to be established. These techniques seek to develop a Reduced-Order Model (ROM), which can successfully replace its heavier counterpart for tasks like design and optimization as well as real-time predictions. These tasks all call for the model to run numerous times, which is typically not possible due to a lack of sufficient and accessible computer resources [3].

So that civil engineers can swiftly research a system's dominant impacts with the fewest possible computational resources, they capture the behaviour of these source models. Because of market demands for quicker design cycles that result in higher-quality goods and structures, ROMs have grown in popularity in the field of civil engineering. ROMs can be used in civil engineering to streamline multiple models created from comprehensive 3D system simulations. Therefore, they can be used by civil engineers to improve the designs of structures and produce more thorough structural simulations [4, 5].

An appropriate orthogonal decomposition

The singular value decomposition (SVD) approach is used to solve partial differential equations (PDEs). Proper Orthogonal Decomposition (POD) is the SVD approach used for PDEs. It ranks among the best dimensionality reduction methods for the analysis of complex spatiotemporal systems. POD-based ROM is still state-of-the-art in model order reduction despite its inception a few decades ago, especially when combined with Galerkin projection [6]. POD is used to extract the dominant spatial subspaces from a dataset. In other words, POD determines the dominant coherent paths in an infinite space that most accurately characterise the spatial evolution of a system. Therefore, there is a strong connection between POD-ROM and either the SVD or eigenvalue decomposition of a snapshot matrix. Figure 4 depicts the development of ROM techniques. [7, 8].

Discussion

The already labour-intensive field of civil engineering design and construction faces a number of difficulties, such as an ageing workforce, rising labour costs, declining productivity, and a shortage of on-site staff. Profits in the industry are impacted by all of these limitations. In these conditions, it is inevitable that some civil engineering and construction operations will be automated using physics-based ML. Applications of physics-based ML in civil engineering depend heavily on data. It is crucial to provide a public data collection for civil engineering as a result. A construction-related dataset may accomplish the same for construction automation, for instance, as a general-

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purpose dataset resembling ImageNet has actively pushed research in the DL field. Researchers can concentrate more on ML models based on physics with these kinds of open data sets. [9].

Conclusion

Since 2000, ML technology has gradually gained prominence in civil engineering and has become more crucial to the development of automated technologies. However, due to their high data needs, failure to generate physically consistent findings, and lack of generalizability to out-of-sample scenarios, the deployment of even the most cutting-edge black-box ML models has frequently met with poor success in the field of civil engineering. The key difficulties are obtaining high-quality data and minimising the effects of the site environment. This paper offers a solution to the data acquisition conundrum after carefully reviewing the literature on the subject. Several teams might work together to create a comprehensive database using the same annotation criteria. Currently, researchers in the field of civil engineering have mostly used ML as a technique.

Currently, ML is mostly used as a method for feature extraction or detection by researchers in civil engineering. In order to address the urgent environmental and physical modelling issues in civil engineering, we believe that combining ML models and physics principles will play a crucial role in the future of scientific modelling. The goal of future research is to completely comprehend physics-based ML and combine it with the particular knowledge domains of civil engineering to create physics-based ML models specifically designed for use in civil engineering applications [10].

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Potential Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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