Optimizing complex modeling processes through machine learning technologies

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Dr. Zohaib Hasnain is applying high-functioning artificial intelligence to physics-based processes in an effort to "automate" modeling. Credit: Texas A&M Engineering

Engineering a spaceship is as difficult as it sounds. Modeling plays a large role in the time and effort it takes to create spaceships and other complex engineering systems. It requires extensive physics calculations, sifting through a multitude of different models and tribal knowledge to determine singular parts of a system's design.

Dr. Zohaib Hasnain's research shows that data-driven techniques used in autonomous systems hold the potential to solve these complex modeling problems more accurately and efficiently. Applying high-functioning artificial intelligence to physics-based processes, he aims to "automate" modeling, reducing the time it takes to produce solutions and cutting production costs.

"If I am trying to undertake something along the lines of, say, designing a pencil, there's a process involved in designing that pencil," Hasnain said. "I have a certain set of steps that I would undertake given the knowledge that I have available to me based on what others have done in the past. Anything that can be described by a process or an algorithm on paper can be automated and analyzed in the context of an autonomous system."

An assistant professor in the J. Mike Walker '66 Department of Mechanical Engineering, Hasnain realized while working in the aerospace industry, the delay in projects due to modeling efforts. While conducting traditional modeling processes, scientists and researchers must create various models, many of which require testing. Additionally, filing through individual models takes far too long to produce answers. An example of a traditional modeling for space systems is computer fluid dynamics, or CFD, which uses numerical analysis to determine solutions, resulting in hefty costs computationally, and in human labor for verification.

"I always thought that there was work to be cut out because there are autonomous systems and machines that seemed capable of handling the bottleneck that is modeling," Hasnain said. "My research is a first step in understanding how and when data-driven techniques are beneficial, with the ultimate goal of taking a process that consumes months or weeks to solve, and producing a solution in hours or days."

Hasnain, accompanied by assistant professor Dr. Vinayak R. Krishnamurthy and graduate research assistant Kaustubh Tangsali, conducted a study to understand how commonly used machine-learning architectures such as convolutional neural networks (CNN) and physics informed neural networks (PINN) fare when applied to the problem of fluidic prediction. The data-driven approach uses a pre-existing modeling database to train a model over carefully controlled variations in fundamental physics of the fluid, as well as geometries over which the fluid flows. The model is then used to make a prediction. Their research found that both CNN and PINN have the potential to optimize modeling processes if targeting very specific aspects of the solution process. They are now working on a hybrid learning approach to achieve their final goal of speeding up the design process.

"We're looking at a different set of tools that will replace the old tools," said Hasnain. "We are trying to understand how these new tools behave in the context of applications traditionally governed by first principles-based solution techniques."

The researchers published their findings in the *Journal of Mechanical Design*. Their article, "Generalizability of Convolutional Encoder-Decoder Networks for Aerodynamic Flow-field Prediction Across Geometric and Physical-Fluidic Variations," focuses on understanding dimensional tools that have the potential of replacing modeling tools that are the current industry standard.

From the research results, Hasnain hopes to build an autonomous infrastructure that pulls from a collection of data to produce modeling solutions through hybrid machine-learning architectures. Through algorithms and pre-existing data, the infrastructure will be a modeling process that can be applied to various systems in real-life applications. Eventually, he plans to share this infrastructure for widespread, free usage.

"I would like this infrastructure to be a community initiative that's offered free to everyone," Hasnain said. "Perhaps more importantly, because it can produce near on-demand solutions as opposed to the current modeling state-of-the-art, which is extremely time-consuming."

The infrastructure is in its early stages of development. Hasnain and his fellow researchers are working to produce a prototype in the near future.

More information: Kaustubh Tangsali et al, Generalizability of Convolutional Encoder–Decoder Networks for Aerodynamic Flow-Field Prediction Across Geometric and Physical-Fluidic Variations, *Journal of Mechanical Design* (2020). DOI: 10.1115/1.4048221

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