


Real-time prediction of wind–fire interaction using a CFD-based deep neural network framework: A methodological approach

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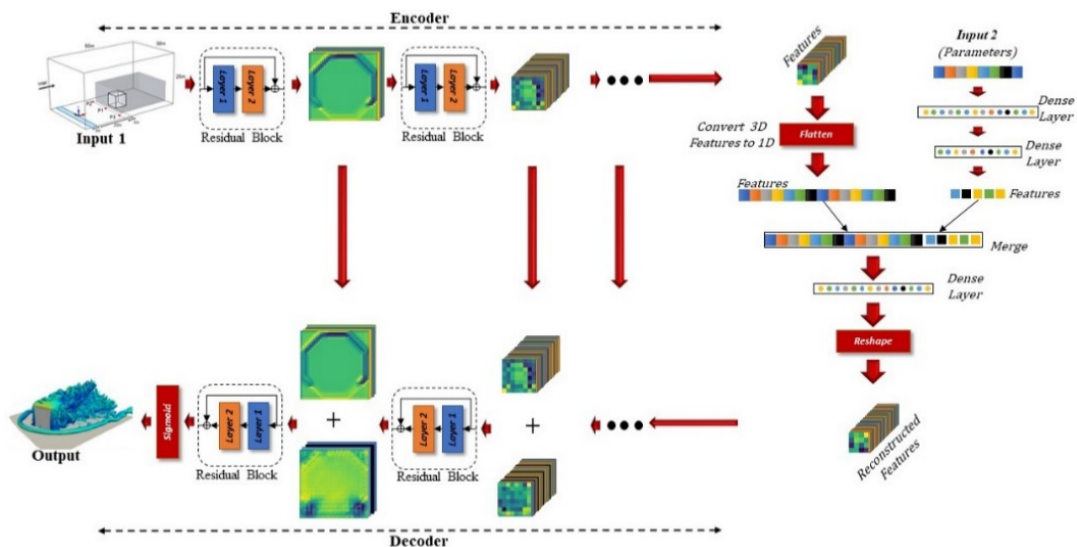
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Abstract: Bushfires have long been a recurrent and devastating problem in Australia, with the 2019/20 season standing out as one of the worst on record, resulting in a tragic loss of life and property. The combination of wind and fire can lead to catastrophic outcomes, particularly in the case of fire-enhanced wind or wind-fire, where the intense heat of the flames fuels strong airflow, ultimately resulting in massive destruction. Accurate prediction of the behaviour of wind-fire is crucial for effective bushfire management and forecasting tools, as well as for making informed safety decisions.

Although computational fluid dynamics (CFD) and in general physics-based models have proven useful in simulating fire dynamics and predicting fire-enhanced wind, their computational intensity and physical domain restrictions pose significant limitations. CFD models require the calculation of millions of equations in small time steps, which can be highly resource intensive. Furthermore, these models typically have restrictions in the physical domain, and can only simulate small areas of a few tens of meters in size, requiring several days of computation. Consequently, CFD models may not be suitable for real-time decision-making and fire management tasks, which require quick and accurate predictions of wind-fire behaviour. To overcome these limitations, there is a growing need to develop innovative methods that can predict wind-fire behaviour in real-time using advanced machine learning techniques, such as deep neural networks (DNNs).

This study employed a DNN to gain insight into the convection heat transfer of a 2D small wind driven pool fire. The generated dataset consisted of two wind velocities and featured a square geometry with a fixed sized pool fire. The aim was for the convolutional DNN to learn about two-dimensional wind-driven convection heat transfer without prior knowledge of the underlying partial differential equation. The mean square errors (MSE) loss function, specifically designed for the physics of convection heat transfer, was used. The training, testing, and validation of the DNN involved using 60%, 20%, and 20% of the CFD created profiles/images.

The findings of this study indicated that DNNs can learn physical problems without requiring knowledge of the fundamental governing equation.



Keywords: Wind–fire interaction, computational fluid dynamics, deep neural networks, machine learning