Subgrid stress tensor modeling in homogeneous isotropic turbulence using 3D convolutional neural network

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Numerical simulation of Turbulence is one of the classical approaches for studying active scales dynamics in a turbulent flow. The interactions between the different scales of motion featured by any turbulent flow is intractable with present knowledge and computer power. To bypass these difficulties, numerical models with a reduced number of freedom degrees such as Large Eddy Simulation (LES) have been proposed. In this approach, large-scale motions are solved using the large eddy equations whereas small-scale influence is modeled and injected into the large-scale dynamics. Recently, artificial intelligence (AI) methods have been proposed to model unresolved scale impacts on large scale motions. On one hand, this work promotes a more optimal use of the AI potential and, on the other hand, it provides a framework which allows to deal with the variety of scales. We use an optimized U-net shaped convolutional neural network (CNN) for the learning of the stress tensor which describes the non resolved - resolved as well as the non resolved - non resolved interactions, from the 3D raw filtered velocity field. We show that the present model is one of the most accurate solutions that has been proposed so far, for the prediction of the stress tensor as well as for its derived quantities namely the divergence and its contraction with the filtered strain rate tensor. The AI based quantities correlations with their expected counterparts oscillate between 90 and 99%, outperforming the Clark model. This performance is neither bound to the simulation used for the learning nor to its Reynolds number. We highlight that the machine learning based model accuracy doesn't seem to be affected by the increase of the Reynolds number by 50 or almost 200%. This confirms that the machine learning model inferred a physics compatible mapping between the filtered velocity field and the stress tensor. This coupling widens computational fluid dynamics' scope and proposes to overcome the limitations of our current understanding of the physics and computer capacity to build faster and more reliable numerical models.