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Geoscientific Model Development Discussions

Interactive comment on "Development of a large-eddy simulation subgrid model based on artificial neural networks: a case study of turbulent channel flow" *by* Robin Stoffer et al.

Anonymous Referee #1

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1 General comments

The manuscript "Development of a large-eddy simulation subgrid model based on artificial neural networks: a case study of turbulent channel flow" (gmd-2020-289) by Stoffer et al. describes the training and testing of an artificial neural network (ANN) intended to act as a a large-eddy simulation (LES) subgrid-scale (SGS) turbulence closure model. The ANN was trained on filtered direct numerical simulation (DNS) fields, then compared to the popular Smagorinsky-Lilly eddy-viscosity model in *a priori* and *a posteriori* applications to mock LES fields (previously unseen filtered DNS fields). The ANN SGS model performs well in the *a priori* case where it is applied offline to a

filtered DNS field, with its predicted turbulent stresses matching those filtered from the DNS much closer than the Smagorinsky-Lilly model both visually in the spatial patterns of the predicted stresses and in their probability distribution and spectrum. The ANN was then implemented in their DNS/LES code (MicroHH) as an LES turbulence closure model for the *a posteriori* test, but was unable to dissipate enough fine-scale energy to maintain a stable simulation.

The manuscript is well-referenced and thoroughly rigorous in its development, and their code/parameters are made publicly available for reproduction which is appreciated. However, the experiment and results presented are not a significant contribution to the literature for a few reasons. Most notably, the ANN was not successful as an LES SGS turbulence closure while being 15-fold more expensive to run than the Smagorinsky-Lilly model, not including the cost of training the ANN or producing the training DNS fields. Further to this point (and as they note), their result that the ANN model generates too much backscatter and not enough dissipation has been both seen and addressed with different methods in the literature. The ability of the ANN to predict accurate SGS stresses based on filtered velocity fields in an *a priori* setting and the analysis of which input fields the ANN deems important to achieve these accurate results is an interesting avenue which could be a valuable contribution to the turbulence-modeling literature, but it is not pursued deeply enough currently to warrant publication.

Recommendation: Major revisions

2 Specific comments

2.1 Focus is too broad and unbalanced

The presentation is divided relatively evenly between the methodology for filtering the DNS fields for the specific finite-volume filter including numerical errors, the training of the ANN, the ANN-produced *a priori* stress fields, the permutation feature importance of the ANN in the *a priori* experiment, and the *a posteriori* results and potential explanations of the observed instability. The result is a very broad outline of the developed ANN SGS turbulence closure with a long description of the methodology and relatively sparse analysis of the results, which would be more appropriate if the model was completely novel or more successful as a functional LES turbulence closure, or both. I recommend that the authors pick one aspect to focus on and thoroughly analyze for this submission and potentially revisit the others separately. The description of the finite volume filtering is particularly verbose with ten full lines dedicated to equations and could be greatly reduced unless the filtering process is decided to be the focus of the manuscript.

2.2 Only one test case

The ANN is trained on fields from a single neutral DNS case at steady state then evaluated on steady-state fields from the same DNS case. The performance of the ANN in the *a priori* test would be much more striking if it were demonstrated that it was able to accurately model SGS stresses for a case that it was not trained on, or even if it was still evaluated for a case it was trained with but shown that the ANN maintains its performance when trained on multiple cases. Put another way, it is not clear here if the ANN is learning about turbulence in general or about a single steady-state field specifically, which makes the results difficult to properly digest. The potential insights into turbulence modeling from the analysis of permutation feature importance could be quite interesting if it is shown that there is some generality to the ANN.

2.3 Unstable when used as a live model

The result that the ANN SGS model leads to an unstable LES solution is not worthy of publication. I suggest that the authors either re-focus the manuscript on the implications of what can be learned from the *a priori* results or implement some of the possible solutions that they mention (e.g. limiting backscatter, adding dissipation via an eddy-viscosity component) to achieve numerical stability and discuss the implications of the amount of tuning necessary to, for example, their unique filtering process including numerical errors or the general formulation of mixed models (which are often very ad hoc and could use insights from new sources).

2.4 Minor comments

- A formulaic description of your implementation of the Smagorinsky-Lilly model and its associated wall model would be helpful
- Table 3 would be more digestible as a figure
- Dissipation ($-\tau_{ij}S_{ij}$) would be nice to see in the analysis of the *a priori* results, particularly given the low energy in the Smagorinsky-Lilly results for just τ_{ij} and the *a posteriori* outcome for the ANN
- Line 206: “Simply boils down to...” is overly casual

3 Technical corrections

- Fig. 2: The titles on the individual fields are much too small to read at 100% resolution

- Line 366: “For the u-input stencil the u-velocity input stencil”

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