Compound Parameterization for a Quality Control of Outliers and Larger Errors in NN Emulations of Model Physics

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1. Introduction

We have developed NN emulations of the long wave radiation (LWR) and short wave radiation (SWR) parameterizations [1,2,3] which are the most time consuming components of model physics of the National Center for Atmospheric Research (NCAR) Community Atmospheric Model (CAM).

The developed highly accurate NN emulations for LWR and SWR are two orders and one order of magnitude faster than the original/control NCAR CAM LWR and SWR, respectively [1,2,3]. The NN emulations use 50 neurons (NN50) for the LWR NN emulation and 55 neurons (NN55) for the SWR NN emulation in the hidden layer. They provide, if run *separately* at every model physics time step (1 hour), the speed-up of ~ 150 times for LWR and of ~ 20 times for SWR as compared with the original LWR and SWR, respectively [1,2,3].

The results of decadal climate simulations performed with NN emulations for both LWR and SWR, i. e., for the full model radiation block, have been validated against the parallel control NCAR CAM simulation using the original LWR and SWR. The almost identical results have been obtained for these two parallel 40-year climate simulations [4].

Larger errors and outliers (i.e. a few extreme errors) in NN emulation outputs have a very low probability (as will be shown in Fig. 1 below) and are distributed randomly in space and time. However, when decadal climate simulations are performed using NN emulations, the probability of obtaining larger errors may increase. As we learned from our experiments with NCAR CAM, the model was robust enough to filter out such randomly distributed errors, without their accumulation in time. However, for such a highly non-linear system as a climate model, it is desirable to introduce a quality control (QC) mechanism, which could predict and eliminate such errors during long-term model integration, not relying upon the robustness of a model that can vary significantly from one model to another. Such a mechanism would make our NN emulation approach more robust and generic. We introduced such a QC technique the combination of which with the NN emulation is called a compound parameterization (CP).

2. The Compound Parameterization Approach for Reduction of the Number and Probability of Larger Errors and Outliers in NN Emulations of Model Physics

CP consists of the following three elements: the original parameterization, its NN emulation, and a QC block. A nonlinear and effective QC design is based on training, for each NN emulation, an additional NN to specifically predict the errors in the NN emulation outputs for a particular input. During a routine climate model simulation with CP using NN emulation, the QC block determines at each time step of model integration and at each grid point whether the NN emulation or the original parameterization has to be used to generate physical parameters (i.e. parameterization outputs). Namely, when the NN emulation errors are too large for a particular grid point and time (i. e. if they exceed a predefined error

threshold) the original parameterization is used instead of NN emulation. In this case, inputs and of original parameterization outputs the can be saved to further adjust the NN emulation. Namely, after accumulating a sufficient number of these records, an adjustment of the NN emulation can be produced by a short retraining using the accumulated input/output records. Thus, the NN emulation becomes adjusted to the changes and/or new events/states produced by a complex climate model system.





Fig.1. Probability density distributions of emulation errors for the SWR NN55 emulation (solid line) and for the SWR CP (dashed line). Both errors are calculated vs. the original SWR parameterization on the independent test set. Vertical axis is logarithmic.

two error probability density functions. It demonstrates the effectiveness of CP. Namely, application of CP reduces probability of medium and large errors by about an order of magnitude. Only the errors below the predetermined threshold are allowed during climate model simulation with CP. It is noteworthy that at each time step throughout the entire 40-year model simulation the NN emulation outputs were rejected by the QC and the original parameterization was used instead mostly for 0.05% - 0.1% but not more than for 0.4% - 0.6% of model grid points. Therefore, the computational performance of the model with NN emulation was practically not reduced and CP is still about 20 times faster than the original SWR parameterization.

3. Conclusions

A new CP approach is developed. It is applied to NN emulations of the SWR parameterization in NCAR CAM. When using CP for the highly non-linear climate model, practically all large and medium-large errors can be reliably controlled during long-term climate simulations.

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