Fast and Accurate Neural Network Emulation of the NCAR CAM-3 Short Wave Radiation Parameterization: Evaluation of Accuracy of Approximation and Computational Performance

Vladimir M. Krasnopolsky,
Earth System Science Interdisciplinary Center, University of Maryland and SAIC at NCEP/NOAA, USA
Phone: 301-763-8000 x 7262, Fax: 301-763-8545, Email: Vladimir.Krasnopolsky@noaa.gov
Michael S. Fox-Rabinovitz, and Dmitry V. Chalikov
Earth System Science Interdisciplinary Center, University of Maryland, USA

A new approach using neural networks (NN) has been recently developed by the authors for emulating model physics in numerical climate and weather prediction models. This NN approach has been applied first to the long wave radiation (LWR) parameterization in NCAR CAM as the most time consuming part of model physics [*Krasnopolsky et al. 2005*]. The NN emulation of the atmospheric LWR parameterization is fast (about 80 times faster than the original LWR parameterization) and accurate (with practically negligible bias and small rms deviations from the original LWR parameterization). The short wave radiation (SWR) is the second most time consuming part of model physics calculations. In this study, we applied the NN approach to NCAR CAM-3 SWR parameterization. The preliminary evaluation of the NN emulations developed for NCAR CAM-3 SWR parameterization is presented below.

NN approximations of model physics are based on the fact that any parameterization of physics can be considered as a continuous or almost continuous mapping (input vector vs. output vector dependence), and NNs are a generic tool for approximation of such mappings [*Krasnopolsky et al. 2002*]. NN is an analytical approximation that uses a family of functions like:

(1)
$$y_q = a_{q0} + \sum_{j=1}^{k} a_{qj} \cdot f(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i); \quad q = 1,2,\ldots,m$$

where x_i and y_q are components of the input and output vectors respectively, a and b are fitting parameters, and f is a so called activation function (usually it is a hyperbolic tangent), n and m are the numbers of inputs and outputs respectively, and k is the number of neurons in the hidden layer (for more details see appendix in [*Krasnopolsky et al., 2002*]).

The function of the SWR parameterization in atmospheric GCMs is to calculate heat fluxes cased by SWR processes in the atmosphere. In the NCAR CAM SWR parameterization [*J. of Clim. 1998 and the references to W. Collins therein*] used in this study, the calculations of cloudiness are completely separated from the calculations of radiation effects. Due to such a structure convenient for developing NN emulation, we are able to approximate the entire SWR parameterization with only one NN, with cloudiness used just as one of the NN inputs.

Both the original SWR and the NN developed for approximation of the SWR parameterization have 101 inputs (n = 452 in eq. (1)), which include twenty profiles (specific humidity, ozone concentration, relative humidity, fractional cloud cover, in-cloud cloud ice water path, in-cloud cloud liquid water path, liquid effective drop size, ice effective drop size, interface pressure, 12 profiles of aerosol mass mixing ratios) and seven relevant surface characteristics (including cosine of solar zenith angle). This NN has 26 outputs (m = 26 in eq. (1)): a profile of the heating rates (HRs) $\{q_k\}_{k=1,\ldots,26}$. Note that NCAR CAM-3 has 26 vertical levels. The developed NN emulations have one hidden layer with either 50 (NN50) or 100 (NN100) neurons (k = 50 or 100 in eq. (1)) that provide the sufficient accuracy of approximation.

For these initial experiments, a representative data set consisting of about 300,000 input/output combinations has been generated using the two-year NCAR CAM-3 simulation. It was divided into three parts each containing about 100,000 input/output combinations. The first part was used for training, the second one was used for tests (control of over-fitting, control of a NN architecture, etc.), and the third part (the second year) was used for validations only.

Table 1 shows a bulk validation statistics for the accuracy of approximation of our NN emulation for SWR, and also the comparison with the accuracy of the corresponding NN emulation for LWR [*Krasnopolsky et al., 2005*]. NN emulations have been evaluated against the original parameterizations. For calculating the error statistics presented in Table 1, the original parameterization and its NN emulation have been applied to validation data. Two sets of the corresponding HR profiles (for the original parameterization and its NN emulation) have been generated. Bias and RMSE presented in Table 1 have been calculated as the mean and root mean square differences between these two sets of HRs. Mean values and standard deviations (s) of HRs are also presented for a better understanding of relative errors. As mentioned above, our NN emulation for LWR performs about 80 times faster than the original LWR parameterization. Our NN emulation for SWR is approximately two times more complex (has more inputs). As a result it performs about 40 times faster than the original SWR parameterization.

Table 1. Accuracy of Heating Rates (in K/day) calculated using NN Emulations for SWR and LWR for NCAR CAM-3 vs. their Corresponding Original Parameterizations. Mean values and standard deviations (s) of HRs are also presented.

NN	Radiation	Bias	RMSE	Mean HR	σ HR
NN50	SWR	$2.\times10^{-3}$	0.31	1.47	1.90
	LWR	$1.\times10^{-3}$	0.38	-1.43	1.76
NN100	SWR	$2.\times10^{-4}$	0.25	1.47	1.90
	LWR	$4.\times10^{-4}$	0.33	-1.43	1.76

The obtained results show that the NN emulation of the considered atmospheric SWR parameterization is highly accurate and provides a significantly improved computational efficiency. Using both NN emulations for LWR and SWR will result in a significant, about 40-80 times, acceleration of calculations of the entire radiation block.

The further complete reexamination of computations for all model physics components in NCAR CAM-3 will be done later. This in turn will potentially make a positive practical impact on extensive experimentation with this kind of complex models needed for improving climate change assessments and weather prediction. The developed methodology can be applied to other LWR and LWR schemes used in the variety of models, process studies, and other applications.

The parallel NCAR CAM decadal climate simulations, performed with the original LWR parameterization and its NN emulation, are very close to each [*Krasnopolsky et al., 2005*]. Similar decadal experiments are planned for SWR of NCAR CAM-3.

Acknowledgments. The authors would like to thank Drs. W. Collins, P. Rasch, and J. Tribbia (NCAR) for useful discussions and consultations.

References

Journal of Climate, 1998: v. 11, No. 6 (the special issue).

Krasnopolsky, V.M., M.S. Fox-Rabinovitz, and D.V. Chalikov, 2005: “Fast and Accurate Neural Network Approximation of Long Wave Radiation in a Climate Model”, *Monthly Weather Review*, in press,

Krasnopolsky V. M., D. V. Chalikov, and H. L. Tolman, 2002: "A Neural Network Technique to Improve Computational Efficiency of Numerical Oceanic Models", *Ocean Modelling*, v.4, 363-383