Proceeding Series of the Brazilian Society of Computational and Applied Mathematics, v. 8, n. 1, 2021.

Trabalho apresentado no XL CNMAC, Evento Virtual - Co-organizado pela Universidade do Mato Grosso do Sul (UFMS).

Proceeding Series of the Brazilian Society of Computational and Applied Mathematics

An MLP-P_1 model for indirect temperature predictions from total incident radiation measurements

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In this work we present an artificial neural network (ANN) model for indirect temperature predictions from total incident radiation measurements in a given participating media. The inverse radiative heat transfer problem is set as a regression problem that has the total incident radiation measurements as dependent variables. As a test case, the problem is set in an one dimensional domain $D = [a, b]$ and a linear temperature distribution is assumed, $T(x) = \alpha + \beta x$, $x \in D$, with α known *a priori*.

The regression model is built as a Multi-layer Perceptron (MLP) artificial neural network model [2]. Following a supervised training strategy, the MLP is calibrated from known n_{train} samples selected for this end. Any given j-th sample is a pair $X_k = (\{\Phi_i^{(k)}\}_{i=0}^{n_v-1}, \beta_k)$, where $\Phi_i^{(k)} = \Phi^{(k)}(x_i)$ is the total incident radiation measured at the vertex $x_i \in D$, and n_v is the fixed number of vertices (measurement's locations).

Each calibration sample X_K has been built by choosing the β_k and, then, computing $\Phi^{(k)}$ by solving the direct radiative heat transfer problem. The P_1 approximation [1, 3, 5] has been used to compute the total incident radiation. Once the calibration set has been computed, the MLP can be calibrated. The MLP has been computed using the machine learning Python package `scikit-learn` [6]. The SP_1 approximation has been computed using the finite element Python package `FEniCS` [4].

The validation of the MLP model has been performed by applying n_{valid} validation samples. Here, each validation sample $j = 0, 1, \ldots, n_{valid}$ has been built by randomly fixing the β_k value and, then, the related $\Phi^{(k)}$ has been computed from the P_1 approximation of the direct radiative heat transfer problem.

Our tests have produced very good results. For instance, lets considered the case of $D = [0, 1]$, a homogeneous medium with the scattering coefficient $\sigma = 1$, the absorption coefficient $\kappa = 1$, and temperature $T(x) = 1000 + \beta x$, $0 \leq \beta \leq 1000$. For this case, we have built a calibration set with $n_{\text{train}} = 11$, $\beta_k = 100k$, $k = 0, 1, \ldots, n_{\text{train}} - 1$, and $\Phi_i^{(k)} = \Phi^{(k)}(x_i)$, where $x_i = 0.25i$, $i = 0, 1, \ldots, n_v - 1$, $n_v = 5$. Here, a MLP with 5 hidden neurons (one hidden layer) has been sufficient to reach a calibration curve with $R^2 = 0.99$. The MLP has been then validated using a validation set with 25 random samples with $0 \leq \beta_j \leq 1000$. Again, a very good validation curve has been found with $R^2 = 0.99$. The results indicates the potentiality of the proposed methodology to the indirect temperature prediction from total incident radiation measurements.

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Acknowledgment

This study was financed in part by the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), finance program PIBIC CNPq-UFRGS.

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