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An MLP-P_1 model for the scattering coefficient estimation from total incident radiation measurements

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In this work we present an artificial neural network (ANN) model for the scattering coefficient estimation from total incident radiation measurements in a participating media. The inverse radiative heat transfer problem is set as a regression problem that has the total incident radiation measurements as dependent variables. The heat transfer is assumed to be modeled in an one dimensional domain $D = [a, b]$, in a medium with known absorption coefficient κ and heat radiation source. The scattering coefficient σ is the independent variable.

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 $X_k = (\{\Phi_i^{(k)}\}_{i=0}^{n_v-1}, \sigma_k)$, 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 is built by choosing the scattering coefficient σ_k and, then, computing $\Phi^{(k)}$ by solving the direct radiative heat transfer problem. The P_1 approximation [1, 3, 5] is used to compute the total incident radiation. Once the calibration is 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 σ_k value and, then, the related $\Phi^{(k)}$ is computed from the P_1 approximation of the direct radiative heat transfer problem.

As a test case, lets considered $D = [0, 1]$, a homogeneous medium with the absorption coefficient $\kappa = 1$, and temperature $T(x) = 1000 + 800x$, $x \in D$. For this case, we have built a calibration set with $n_{\text{train}} = 11$, $\sigma_k = 0.1k$, $k = 0, 1, \ldots, n_{\text{train}} - 1$, 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 one hidden layer (5 hidden neurons) 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 $0 \leq \sigma_j \leq 1$. Again, a very good validation curve has been found with $R^2 = 0.99$. The results indicates the potentiality of the proposed methodology as a tool to estimate the scattering parameter of radiative objects.

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