AI-based models for the resolution of the Radiative Transfer Equation

Subject:

The knowledge of the exact temperature distribution is necessary for many industrial processes to control production and the final quality of the products. Radiative exchanges within semitransparent materials such as glass are described beside conductive heat transfer by radiation. This Radiative Transfer Equation (RTE) involves many variables (space, temperature, wavelength, direction) and is consequently difficult to solve. Different methods exist in the literature to solve this equation such as the Discrete Ordinate Method [1] or different approximation models like P_1-Method or Backward Raytracing Technique [2]. These methods enable to solve the RTE with a good accuracy but they require important computing resources. That is the reason, why only simplest approximation technique like the Rosseland-Approximation are still used in industry.

The goal of this PhD is to use AI to build models and obtain fast results for the computation of the radiative energy or flux which then will be included into the heat equation. The ever-increasing rise of computational power creates the opportunity to use the amount of data offered by modern computers, internet and new digital devices. Machine learning (artificial neuronal networks, deep learning, …) is a growing field of research. A review about different applications of data-driven modeling in science and engineering can be found in [3]. Beside pure data-driven concepts hybrid approaches combining physical- and data-based method are of special interest. A first publication about artificial neural networks in radiation heat transfer analysis was published in [4]. Using a feedforward multilayer perceptron (MLP) with two hidden layers the authors investigate an alternative approach to the Monte-Carlo raytracing for heat transfer applications involving diffuse gray enclosures in the absence of a participating media. In [5] an inverse radiative heat transfer problem was investigated using spectral remote sensing. Although this kind of problem is ill-posed, a MLP was able to retrieve temperature and species concentration simultaneously for a gas mixture rom measurements of radiative intensity.

The PhD will start by building and analyzing neuronal network models for one-dimensional radiative heat transfer models in semitransparent participating non-gray media and will then be applied to increasingly difficult problems.

More Detailed Description:

To simulate radiative heat transfer problems, one has to solve beside the well-known heat transfer equation the so-called radiative transfer equation. Whereas the solution of the heat transfer equation is standard, the solution of the radiative transfer equation is much more complicated and due to the high dimensionality and non-linearity very time consuming.

The basic model for radiative transfer is expressed by the Radiative Transfer Equation (RTE)

$$\bar{\Omega}\cdot\bar{\nabla}I(\bar{x},\bar{\Omega},\lambda,T)+\kappa(T,\lambda)I(\bar{x},\bar{\Omega},\lambda,T)=\kappa(T,\lambda)B(T,\lambda), \tag{1}$$

where $I(\bar{x},\bar{\Omega},\lambda,T)$ describes the radiative intensity depending on position $\bar{x}$, direction $\bar{\Omega}$, wavelength λ, and temperature $T(\bar{x},t)$, which depends on position and time t. The absorption coefficient $\kappa(\lambda,T)$ depends on wavelength and temperature. $B(T,\lambda)$ denotes Planck's function.

The divergence of the radiative flux vector

$$\bar{\nabla}\cdot\bar{q}_{rad}(\bar{x},T)=\bar{\nabla}\cdot\left\{\int_{\lambda}\left(\int_{4\pi}I(\bar{x},\bar{\Omega},\lambda,T)\bar{\Omega}d\bar{\Omega}\right)d\lambda\right\}, \tag{2}$$

describes the source term for the heat equation. Using (1), the term (2) can be transformed to

$$\bar{\nabla}\cdot\bar{q}_{rad}(\bar{x},T)=\int_{\lambda}\kappa(\lambda,T)\left(4\pi B(T,\lambda)-\int_{4\pi}I(\bar{x},\bar{\Omega},\lambda,T)d\bar{\Omega}\right)d\lambda, \tag{3}$$

where the term $G(\bar{x},T)=\int_{4\pi} I(\bar{x},\bar{\Omega},\lambda,T)d\bar{\Omega}$ stands for the radiative energy.

Thus, the radiative source term is determined by the following (input) parameters:

$$(\lambda,\kappa(\lambda,T)), \quad T(\bar{x},t)\,. \tag{4}$$

Using these input parameters one has to build and explore neuronal networks to fasten the calculation of the radiative source term $\bar{\nabla}\cdot\bar{q}_{rad}(\bar{x},T)$.

Literature:

[1] Michael F. Modest. Radiative Heat Transfer. Academic Press (2003)

[2] Norbert Siedow, Dominique Lochegnies, Fabien Béchet, Philippe Moreau, Hiroshi Wakatsuki, Nobuhiro Inoue. Axisymmetric modeling of the thermal cooling, including radiation, of a circular glass disk. International Journal of Heat and Mass Transfer, Vol. 89, (2015), 414-424,

[3] Francisco J. Montans, Francisco Chinesta, Rafael Gomez-Bombarelli, J. Nathan Kutz. Data-driven modeling and learning in science and engineering. C. R. Mecanique 347 (2019) 845-855

[4] Mehran Yarahmadi, J. Robert Mahan, Kevin McFall. Artificial neural networks in radiation heat transfer analysis. Journal of Heat Transfer, Vol. 142 (2020) 092801-1:9

[5] Tao Ren, Michael F. Modest, Alexander Fateev, Gavin Sutton, Weijie Zhao, Florin Rusu. Machine learning applied to retrieval of temperature and concentration distributions from infrared emission measurements. Applied Energy 252 (2019) 113448