Scientific machine learning for electromagnetic field computations

Abstract: A recent report by the US Department of Energy defines the area of scientific machine learning as “a core component of artificial intelligence (AI) and a computational technology that can be trained, with scientific data, to augment or automate human skills”, which has “the potential to transform science and energy research”. In this presentation, we discuss the potential of scientific machine learning methods to problems in computational electromagnetics starting from standard electromagnetic structure analysis and multi-physics modeling in the time-domain, employing an unsupervised learning strategy based on Physics-Informed Neural Networks (PINN). PINNs directly integrate physical laws into their loss function, so that the training process does not rely on the generation of training ground truth data from simulations (as in typical neural networks). We demonstrate the unconditionally stable solution of coupled electromagnetic-thermal problems, along with the modeling of frequency selective surfaces and metasurfaces, orders of magnitude faster than the conventional finite-difference time-domain technique (FDTD), *including training time of the neural network.*

Moreover, we demonstrate the impact of machine learning on the computational modeling of radiowave propagation scenarios. We build convolutional neural network models that can process the geometry of indoor environments, along with physics-inspired parameters, to rapidly estimate received signal strength (RSS) maps. Emphasis is placed on the **generalizability** of these models, which is their ability to "learn" the physics of radiowave propagation and produce accurate modeling predictions in new geometries well beyond those included in their training set.