

Abstract: Machine learning versus physics-based modeling

Jose Andino Saint Antonin

Physics-based models (PBMs) rely on the long established principles of conservation of mass, energy and momentum, as well as constitutive laws and equations of state, which add needed information about the relationship between system variables to allow analytic or numerical solutions.

Well-made PBMs enables us to understand and predict complex processes and have already been applied all across our modern society e.g. to predict the orbits of planets, constructing bridges or modelling flow in oil reservoirs.

The advent of large scale computing has brought the possibility of using machine learning (ML) as a prediction tool. Although not based in robust physical principles, ML can be applied to many more problems and sometimes outperform PBMs models.

The type of problem being dealt with plays a major role in the selection of the predictive technique. ML shines in problems where we have no direct theoretical knowledge about the system, but we have a lot of experimental data on how it behaves. Conversely, physics-based models are better at problems that can be described mathematically and where there is quality information about the input to the model.

Even for systems that can be described using a PBMs, ML models can learn to make accurate predictions on them too, if given enough observations. This ability to predict and act through experience (rather than through *a priori* mathematical equations) is not at all surprising. It is well exemplified in how toddlers learn to walk, without any knowledge of physics. Likewise, although highly complex systems may be modelled with knowledge of physics simpler ML models or hybrid models may leaner and make better job predicting the system's behavior. Additionally, ML learning may help us in the discovery phase of physics, when we are trying to find a constitutive law that fits physical observations. Finally, the PBMs which can be very time consuming to run can be used to train simple ML models that perform the trick with almost no computation expense in the domain of their training.

Specific examples of used of ML models in traditionally physics-based problems as well as hybrid approaches are discussed in detail.