Machine Learning (ML) techniques make working with complex systems easy

Some small ANN models are developed to be used as RF tuning, monitoring and virtual diagnostics tools at the ESS in Lund.

The European Spallation Source (ESS) infrastructure is being constructed in Lund, and will be one of the most powerful facilities using neutrons to do research in different fields, like in material structures. The ESS linear accelerator (linac) consists of different accelerating sections to accelerate a beam of protons from zero to 2 GeV kinetic energy through Radio Frequency (RF) cavities before getting collided with a tungsten target to produce neutrons. Tuning the linac in the Drift Tube Linac (DTL) section is of great importance to direct the beam in controlled way to the next sections, but that is hard to achieve because the RF amplitude and phase experienced by the passing beam do not correspond exactly to the ones set by the RF field generator and controller due to some construction-related limitations. As a solution, some diagnostics which are sensitive to time of flight of the beam, like the phase of observed signals in the Beam Position Monitor (BPM) sensors, could be used. Phase differences between the BPMs within the DTL tanks could be calculated to give an indication of how the proton particles are synched with the RF field inside the tanks, but that is normally done in a time-consuming way called RF phase scan. Machine learning (ML) techniques, however, can make life easy, and this is the case for this problem. Having large amounts of available data would make deep learning models a good fit. Developing such models showing the mapping between what we can measure in the DTL tanks, the BPM signals, and what we would like to get information about, the status of the synchronization process between the proton particles and the RF field, is where the tuning of the DTL machine could be done in a few hours instead of a few weeks. However, this mapping is quite complicated and needs different techniques to model it. One of such techniques is multi-shot measurement scenarios, in which instead of measuring the BPM phases as one shot, more shots of measurements are provided to give more information about the process to the models. That is, the data related to all the BPMs are collected all at once and then, as a natural option, after shifting the RF phase and/or the RF amplitude by certain amounts, the second shot of measurement can be taken. That gives significantly better results than the single-shot measurement scenario. There is, however, still a fundamental limitation in the data for the RF amplitude, making its predictions, regardless of model structures, hard to meet the design requirements. The RF amplitude predictions, however, meet the requirements by of 95% confidence, making the models reliable enough for the RF tuning of the machine with some small amount of uncertainty to be considered. On the other hand, the predictions for the RF phase and the input energy to the DTL tank are almost two times better than the requirements. That is of great importance for the input energy because there is no way to measure the input energy in the DTL tanks and the upstream sections in practice, so the models can play the role of virtual diagnostics to give information on this physical property of the beam. The models are small and easy to be deployed in the ESS control system, and that makes the ESS one of the accelerators in the world that is intelligent in this regard. Although a lot of ML-based research has been done in accelerators, just a few have been deployed in the main control systems in accelerators so far; hence, there is a huge possibility to build more advanced intelligent accelerators benefiting from the AI and ML achievements, and this master's project is a step towards that.

Amin Hosseini Nejad

Developing a Machine Learning (ML)-based model for RF tuning of the DTL machine at ESS