Using Artificial Neural Networks to Predict the Magnetization State and Field of a Superconducting Staggered Array Undulator

Sebastian Hellmann
Magnet Group
Paul Scherrer Institute
Villigen, Switzerland
sebastian.hellmann@psi.ch

***Abstract* — Short period undulators, producing high magnetic fields, are an essential component in the production of x-rays in compact free electron lasers (FELs) and medium energy storage facilities. A short-period undulator can be built in different ways, however, the staggered array undulator geometry stands out for its simplicity in design and manufacturing efforts.**

For the operation of a staggered array type undulator, the superconducting material (either *Re*BCO bulks or stacks of 2G *Re*BCO tapes) has to be magnetized in an external magnetic field in order to produce the desired undulator field. Hereby it can be difficult to predict the correlation between the applied external field and the resulting undulator field.

In this publication we a present a possible approach for predicting this complex magnetization process and the consequential undulator field with the help of an artificial neural network. This prediction method can yield results in real time and would therefore be ideal to be used in the control loop of a FEL or a storage ring.

Keywords — undulator operation, superconducting undulator, artificial neural network, HTS magnetization, magnetization currents

I. Introduction

The use of artificial neural networks has steadily increased over the last decades and for a huge variety of different applications. This includes applications such as face and voice recognition, image analysis, video analysis, autonomous and assisted driving, signal analysis and many more.

Artificial neural networks are well suited for finding complex correlations in data, and their application is especially attractive if this correlation is not obvious to spot in the first place.

The application of a neural network as shown here can be divided into three different parts, which will be described in the following:

- Design of the neural network
- Training of the network
- Application of the network

II. Superconducting Undulator magnetization

The operation of a superconducting staggered array undulator requires the magnetization of the superconducting material with the help of an external solenoid. In the example shown here, the assumed solenoid can produce an external magnetic flux density between -10 T and 10 T.

Fig. 1 shows a simulated magnetization process of a staggered array undulator at different time steps and corresponding external magnetic flux densities in the simulation.

The trapped current redistribution and magnetization decay due to flux creep can be seen occurring between time steps “10,000 s” and “18,000 s” as well as between “19,000 s” and “27,000 s”. Between these time steps, the external field is held at the same value. The simulation further shows a possible “accumulation” of magnetization currents in the superconductor, this especially applies for consecutive magnetization steps with different levels of applied external field at reversed polarity. This can be seen in step “19,000 s”, “27,000 s” and “55,000 s” of the simulation.

These two effects make a linear correlation between the applied external field and the resulting undulator field impossible. Artificial neural networks however, are able to be taught even highly nonlinear correlations between inputs and

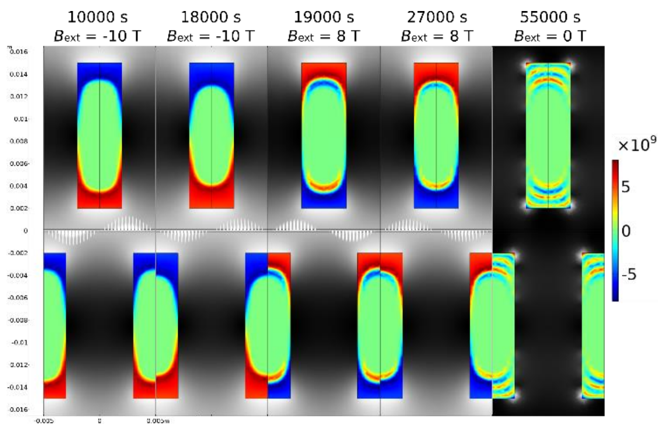

Fig. 1 – Simulated magnetization currents in a single period of a superconducting undulator at different time steps of the simulation.

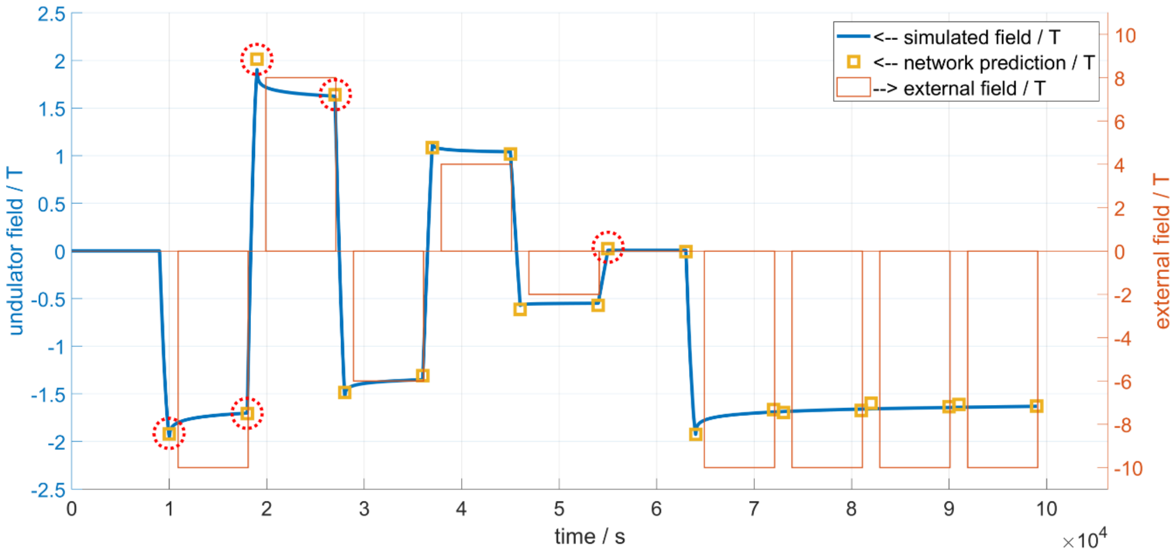

Fig 2. Evaluation of the trained neural network predicting the undulator field depending on the applied external field and the external field history. The dotted circles indicate the time steps depicted in Fig.1

outputs and can therefore be used to predict the undulator field in this example based on the applied external field values only.

III. Network Topology and Training

For the task of predicting the magnetization state and field of a superconducting undulator, a deep cascading-forward neural network is used. The neural network consists of an input layer with ten nodes as inputs for the external field value and an output layer with 20 nodes, ten for the predicted undulator fields after ramping the external field to a new value and ten for the undulator field after the end of an external field plateau. The neural network has two hidden layers with 80 nodes.

To allow the use of the network for the prediction of the magnetization state of a superconducting undulator, the network has to be trained for this task. This can be done with the use of simulation data or measurement data. Here, the generation of the training data is done with the help of a 2D transient COMSOL simulation model. This model is based on the H-formulation and is capable of simulating the magnetization inside the superconducting material of a staggered array undulator. One simulation is executed for an external field profile consisting of ten random external field steps. The generation of one set of training data (10 external field steps plus 20 undulator field values) takes about 50 seconds. With this method, it is possible to generate a large amount of network training data (between 1,000 and 5,000 datasets) in a relatively short amount of time.

Different algorithms are used for comparing the efficiency and speed of the network training with different training datasets. Among the most successful are in this case the “Levenberg-Marquardt” and the “Resilient Backpropagation” training algorithms.

IV. Network Application and Performance

For a meaningful evaluation of the performance of the trained neural network, a dataset, independent from the training dataset has to be used. For this example values for the external flux density are chooses as [-10 8 -6 4 -2 0 -10 -10 -10 -10] T.

Fig. 2 shows the applied external magnetic flux density as red bars and the simulated undulator field as a blue line. The yellow markers depict the undulator field as it is predicted by the neural network for the beginning and end of each plateau of the external field values.

It can be seen that the network can predict the undulator current depending on the value of the applied external magnetic flux density. This also works for the reversal of the magnetization (for example between time step 18,000s and 19,000s).

Fig. 2 further shows, that the trained network can predict the amount of current creep occurring while the external field is held on a constant value. This can be seen for example for the last four steps of the external field values, which are held at a constant value of -10 T.

V. Conclusion

In this example we showed that it is possible to train a deep cascading-forward neural network to “understand” the complex correlation between the applied external flux density (including its history) and the resulting undulator field of a superconducting staggered array undulator.

While the presented results do not always perfectly agree with the simulation data, they clearly show that the neural network can correctly predict the current creep, reverse magnetization and the effects of accumulated magnetization currents in the superconducting bulks of the undulator.