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# MACHINE-LEARNING BASED TEMPERATURE PREDICTION FOR BEAM-INTERCEPTIVE DEVICES IN THE ESS LINAC

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*Abstract*

"*Where there is great power [density], there is great responsibility*"[1]. The concept holds true especially for beam-intercepting devices for the ESS linac commissioning. In particular, beam-intercepting devices will be subject to challenging beam power densities, stemming from proton energies up to 2 GeV, beam current up to 62.5 mA, pulses up to few milliseconds long, and repetition rates up to 14 Hz. Dedicated Monte Carlo simulations and thermo-mechanical calculations are necessarily part of the design workflow, but they are too time-consuming when in need of rapid estimates of temperature trends. In this contribution, the usefulness of a Recurrent Neural Network (RNN) was explored in order to forecast (in few minutes) the bulk temperature of beam-interceptive devices. The RNN was trained with the already existing database of MCNPX/ANSYS results from design studies. The feasibility of the method will be exemplified in the case of the Insertable Beam Stop within the Spoke section of the ESS linac.

## INTRODUCTION

The European Spallation Source (ESS) in Lund (Sweden) is currently one of the largest science and technology infrastructure projects being built today. The facility will rely on the most powerful linear proton accelerator ever built, a rotating spallation target, 22 state-of-the-art neutron instruments, a suite of laboratories, and a supercomputing data management and software development centre [1].

The ESS accelerator high-level requirements are to provide a 2.86 ms long proton pulse at 2 GeV, with a repetition rate of 14 Hz. This corresponds to 5 MW of average beam power, with a 4% duty cycle on the spallation target [2].

A comprehensive suite of beam instrumentation and diagnostics [3] has started to support the commissioning and operation of the normal-conducting linac (NCL) section of the ESS linac. Additional devices and enabling systems are going to be deployed in the superconducting linac (SCL) section, as well as in the transport line to the tuning dump and to the spallation target.

In particular, the Beam Diagnostics Section is responsible for the design, procurement, test and operation of all the bulkiest beam-interceptive devices in both the NCL and SCL linac sections (see the list in Table 1). The beam instrumentation plays the most important role in the machine protection system by monitoring the beam parameters and stopping the beam operation before damages may occur.

Unfortunately, there is no straightforward expression for anticipating the energy deposition of a beam with high power density within accelerator elements, because the deposited energy depends on many beam properties as well as on the material properties of the beam-interceptive device and the capabilities of its cooling system.

Dedicated Monte Carlo simulations and thermo-mechanical calculations in MCNPX [4] and ANSYS [5], respectively, are part of the standard detector design workflow at ESS. However, many relevant beam- and material-related parameters have to be taken into account for the timing consuming simulations and validation. For instance, on a standard laptop it takes several hours to compute the temperature as a function of the time as shown in Fig. 1, when simulating just 14 proton pulses onto the SPK IBS [6].

Table 1: List of the Bulkiest Beam-interceptive Devices in the ESS Proton Linac. (FC = Faraday cup, IBS = Insertable Beam Stop)

| Device | Mean power | Peak Power |
|---|---|---|
| LEBT FC | 0.005 W | 0.0002 MW |
| MEBT FC | 16 W | 0.23 MW |
| DTL2 FC | 170 W | 2.43 MW |
| DTL4 FC | 323 W | 4.63 MW |
| SPK IBS | 411 W | 5.88 MW |
| MBL IBS | 1575 W | 22.5 MW |

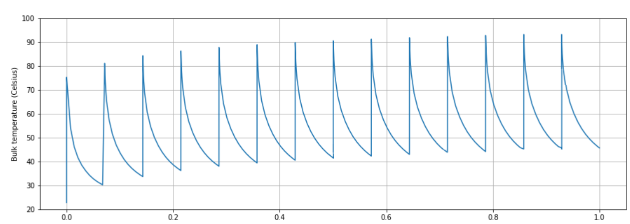


Figure 1: Temperature as a function of the time, calculated in ANSYS for the graphite bulk of the SPK IBS, after 73 MeV protons and 50 µs long pulses, at 6 mA and 14 Hz.

Similarly, dedicated experiments and controlled damage tests are usually expensive and not always an option when the impact(s) of many parameters have to be studied. Therefore, in this contribution a Machine-Learning (ML) based method for the prediction of temperature trends within beam-interceptive devices was developed, not for detector design purposes, but for fast time-series forecasting. In the future, the method described in the next section can be expanded either for standard machine protection purposes or virtual diagnostics.

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[1] cit. Winston Churchill, 1906

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## METHOD

In this contribution, the predictions of temperature trends in beam-interceptive devices of the ESS linac rely on the so-called Long Short-Term Memory (LSTM) model [7].

The LSTM is a processing model of an artificial Recurrent Neural Network (RNN) that nowadays is widely used in the field of deep learning for processing not only single data points, but especially sequential data e.g. weather, financial data, audio and text. The LSTM model exploits feedback connections and can store information over a period of time. In fact, the memory capability results from gates that determine whether information is stored or discarded. In this way it is possible to disentangle long-term and short-term memories, as peculiar as human brains.

The method of this contribution is written in python 3; the main library for developing and testing the method is Keras of TensorFlow 2. The training of the RNN is performed on the basis of the MCNPX/ANSYS database, available from past workflow for detector design. The three dimensional energy deposition was in fact previously calculated in MCNPX and then post-processed in ANSYS to compute the temperature as a function of the time.

The MCNPX/ANSYS database includes the temperature trends in the bulk of the beam-interceptive devices, as a result of the seven possible beam modes at ESS (see the list in Table 2). All the MCNPX calculations considered in the present work were performed after 73 MeV protons; the proton beam is assumed to have a Gaussian distribution in both transverse planes and in all the cases the beam dimensions were always the same.

The output MCNPX file has four columns (i.e. the calculated energy deposition value and the three coordinates of the voxel in which the energy deposition is calculated), whereas the ANSYS output has two columns (i.e. the calculated temperature vs. time). The ANSYS data were interpolated and normalized (between 0 and 1).

The method was optimized by means of the Adaptive Moment Estimation optimizer, also known as ADAM [8]. Tests were performed with 20 epochs and the loss was calculated as Mean Square Error (MSE).

Table 2: List of Beam Modes in the MCNPX/ANSYS Database (C = commissioning, T = tuning)

| Mode | Current (mA) | Pulse (µs) | Rate (Hz) |
|---|---|---|---|
| Probe | 6 | 5 | 1 |
| Fast C | 6 | 5 | 14 |
| RF test | 6 | 50 | 1 |
| Stability test | 6 | 50 | 14 |
| Slow C | 62.5 | 5 | 1 |
| Fast T | 62.5 | 5 | 14 |
| Slow T | 62.5 | 50 | 1 |

## RESULTS

Temperature trends in beam-interceptive devices were predicted with an RNN combined with the LSTM model. In this section, the results after 73 MeV protons onto the SPK IBS are reported as representative example. In the following, the proton beam current is 6 mA, the repetition rate is 14 Hz and the pulse duration is 50 µs.

Several tests were performed in order to determine the useful number of training and validation points, in the sense that: the processing time is approximately just one minute (and not hours like for the full ANSYS simulations) and the uncertainty on the temperature is below 20°C. Three test cases are reported in Table 3 to summarize these initial tests. In the case C, one can notice that just three pulses actually calculated in ANSYS were used for the training.

Figure 2 shows the training loss as well as the validation loss, as calculated for the case C with the ADAM optimizer. Finally, the comparison between the ANSYS results and the results of LSTM-based method is plotted at the top of Fig. 3. The difference between the two datasets is plotted at the bottom of Fig. 3. It is possible to observe that the LSTM model predicts the rising and falling periods with uncertainty less than 2°C, whereas in correspondence of the local maxima, the prediction can be off by up to 16°C. More advanced pre-processing, interpolation and segmentation will be explored with the aim of reducing the discrepancies at local maxima.

Table 3: Summary of tests carried to determine the number of training and validation points. The corresponding number of proton pulses are reported for reference.

| | A | B | C |
|---|---|---|---|
| Training Points | 7k | 14k | 21k |
| Validation Points | 10k | 20k | 30k |
| Pulse Number | 1 | 2 | 3 |
| Processing time | 46 sec | 58 sec | 62 sec |
| ANSYS/LSTM max diff. | 30°C | 26°C | 16°C |

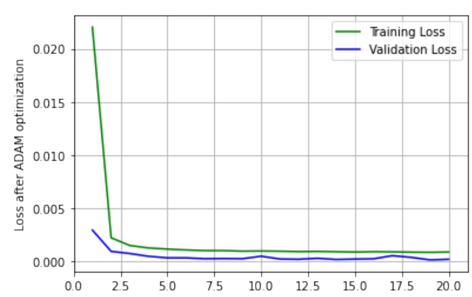


Figure 2: The training and validation loss for the CASE C in Table 3, by means of the ADAM optimizer.

The results are useful for various reasons: firstly, the saturation temperature is obtained within just one minute, so several hours of computational time in ANSYS can be

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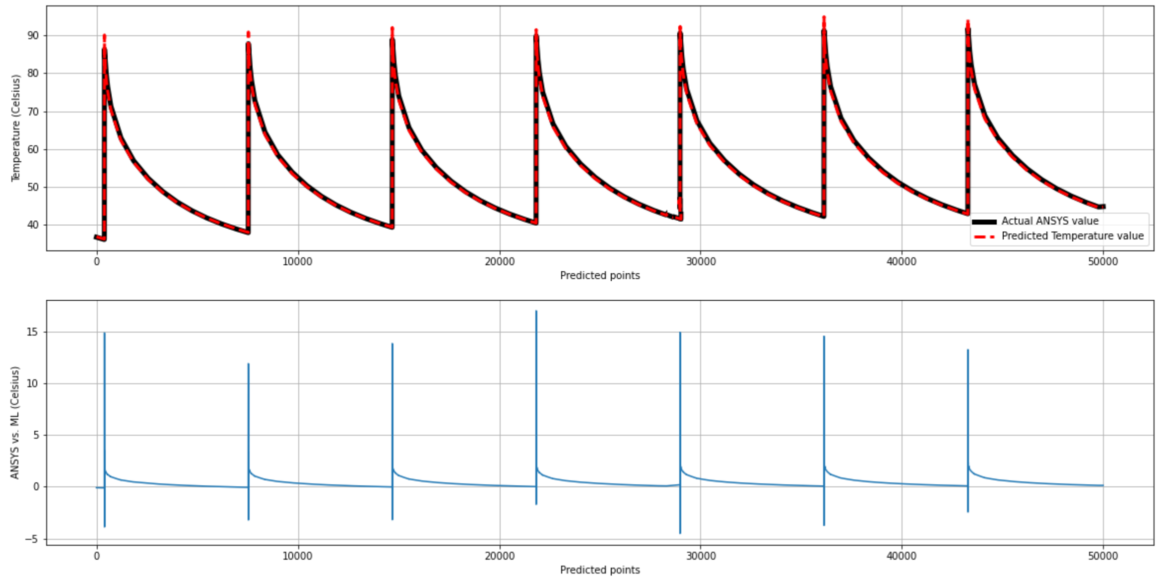


Figure 3: (Top) Comparison between temperature values calculated in ANSYS and those predicted by the Machine-Learning based method presented in this contribution (Bottom) Temperature difference between the ANSYS and the ML-results.

spared. Secondly, the precise temperature values in the rising and falling period can be used for further calculations of temperature trends for pulses shorter than the 50 $\mu$s (i.e. the pulse duration hereby considered for the example in Fig. 3) and for anticipating the impact of the temperature rise in materials close to or insulating the detector bulk. Thirdly, the results set also the reference limit after 14 Hz, thus they can be used to infer temperature trends at lower repetition rates.

## CONCLUSIONS AND OUTLOOK

The protection of the machine and beam-interceptive diagnostics devices is of paramount importance in high power accelerators. For a quick estimation of temperature trends in beam-interceptive devices, there is no straightforward alternative to the standard simulation tools. Therefore, this paper proposed for the first time at ESS an ML-based model that can predict within few minutes the bulk temperatures in beam-interceptive devices of the ESS proton linac. The predictions are made by means of RNNs and in particular the LSTM processing model [7].

The data training and benchmarking were performed with data available from the MCNPX/ANSYS calculations for the design workflow previously outlined in [6]. The results show that the ML-based method accurately computes the rising and falling temperature trends with an error below 2°C in comparison to the reference ANSYS calculations. Local maxima come with a prediction error up to 16°C, therefore more advanced data pre-processing, interpolation and segmentation techniques will be considered to reduce such discrepancy. The method can be used for further studies at shorter pulse durations and lower repetition rates.

In the future, the method can be further expanded to e.g. build extensive look-up tables for routine checklists, develop a low-latency network for ML-based machine-protection systems or virtual diagnostics.

## ACKNOWLEDGMENTS

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