Machine-Learning Based Temperature Prediction for Beam-Interceptive Devices in the ESS Linac

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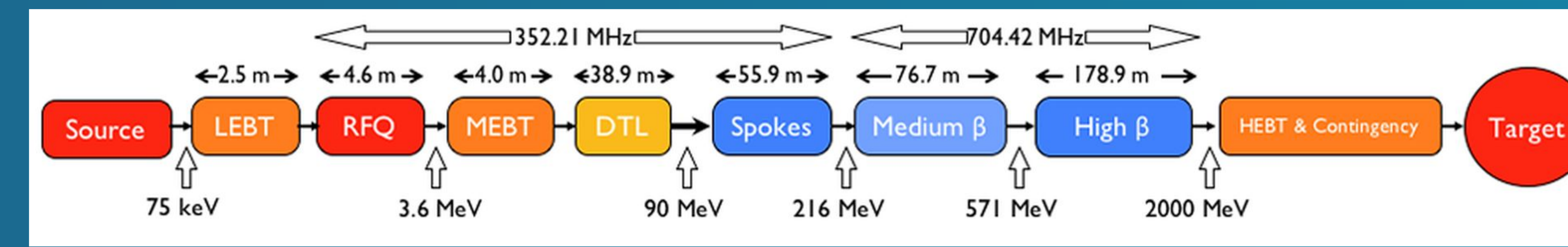
TUPP37

IBIC 2021
International Beam Instrumentation Conference

EUROPEAN SPALLATION SOURCE



Abstract

"*Where there is great power [density], there is great responsibility*" (cit. Winston Churchill, 1906). 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 currents 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 tab.1).
The beam instrumentation plays the most important role in the machine protection system of the ESS proton linac, by monitoring the beam parameters and stopping the beam operation before damages may occur.

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

TAB.1 - List of the bulkiest beam-interceptive devices in the ESS proton linac, as well as mean and peak beam power at the devices' locations. (FC = Faraday cup, IBS = Insertable Beam Stop).

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 detector design workflow at ESS. However, many relevant beam- and material-related parameters have to be taken into account; in addition, both simulations and calculations are time-consuming. For instance, on a standard laptop it takes several hours to compute within the SPK IBS [6] the temperature trend in fig.1.

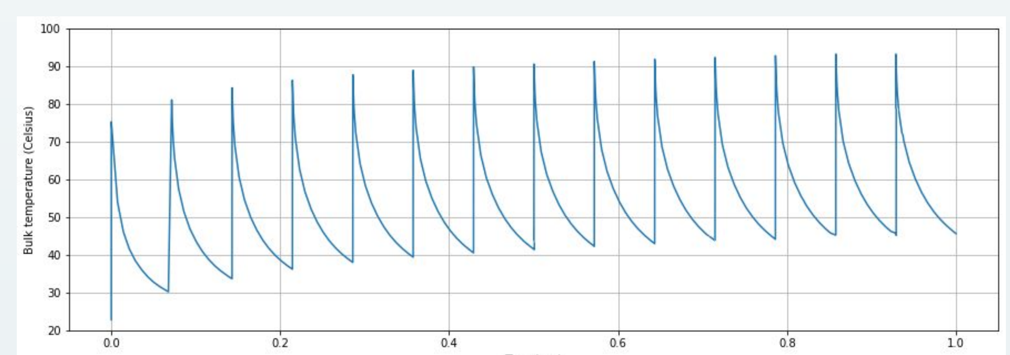


FIG.1 - Temperature as a function of the time, calculated in ANSYS for the graphite bulk of the SPK IBS (50μs long proton pulses, 6 mA, 14 Hz and 73 MeV).

Dedicated experiments and controlled damage tests are usually expensive and not always an option. Therefore, in this contribution a machine-learning 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.

Methodology

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].
An LSTM is a processing model of **artificial Recurrent Neural Networks** (RNNs) 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 method 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 starting from the MCNPX/ANSYS database, available from past workflow for detector design. 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 tab.2). In all the tests, the proton beam has a Gaussian distribution in both transverse planes and has always the same beam dimensions. The ANSYS data are interpolated and normalized (between 0 and 1). The **Adaptive Moment Estimation** optimizer (ADAM) [8] is used. Tests are performed with 20 epochs and the loss was calculated as Mean Square Error (MSE).

Beam mode	Current (mA)	Pulse (us)	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

TAB.2 - List of beam modes in the MCNPX/ANSYS database (C = commissioning, T = tuning).

Results

Temperature trends in beam-interceptive devices were predicted with an RNN combined with the LSTM model. The results after 73 MeV protons onto the SPK IBS are reported as representative example, with 6 mA proton beam current, 14 Hz rate and 50 μs long pulses.
Tests were conducted to determine the useful number of training and validation points while keeping the processing time of few minutes and the uncertainty on the temperature below 20 °C. Tab.3 reports three indicative tests. In the case C, one can notice that just three pulses actually calculated in ANSYS are enough for the model training.

	A	B	C
Training points	7k	14k	21k
Validation points	10k	20k	30k
Pulse number	1	2	3
Processing	46 sec	58 sec	62 sec
ANSYS vs. LSTM	30 °C	26 °C	16°C

TAB.3 - Summary of tests to determine the number of training and validation points.

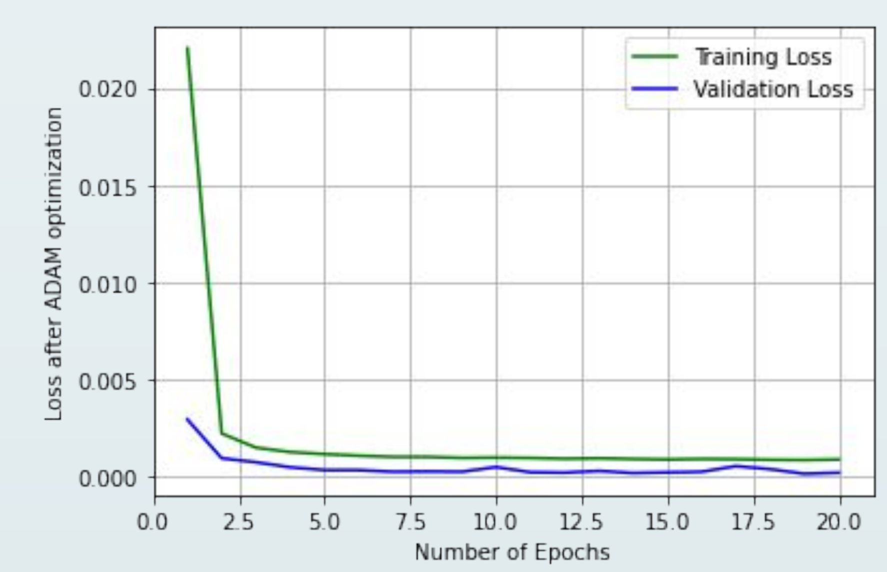


FIG.2 - The training loss as well as the validation loss, as calculated for the case C in tab.3 with the ADAM optimizer.

Finally, the comparison between the ANSYS values and the LSTM model results are shown at the top of fig.4, with the difference between the two datasets plotted at the bottom of fig.4.

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.

The results are useful for the following reasons:
1) The saturation temperature is obtained **within approx. 1 minute**, so several hours of computational time can be spared.
2) The resulting temperature values for the **rising and falling periods** can be used for further calculations of temperature trends for pulses shorter than the 50 μs (i.e. the pulse duration hereby considered for the example in fig.4).
3) The results set the **reference limit after 14 Hz**, thus they can be used to infer temperature trends at lower repetition rates.

Conclusions & Outlook

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

The data training and benchmarking was performed with data available from the MCNPX/ANSYS calculations from the design workflow previously outlined in [6]. The results show that the Machine-Learning based method accurately computes the rising and falling periods with an error below 2 °C. Local maxima come with a prediction error below 20°C. More advanced data pre-processing, interpolation and segmentation techniques will be considered to reduce such discrepancy. The method can be used for extrapolating temperature trends e.g. at shorter pulse durations and lower repetition rates.
In the future, the method can be further expanded to build extensive look-up tables for routine **checklists**, develop a low-latency network for **ML-based machine-protection systems** or **virtual diagnostics**.

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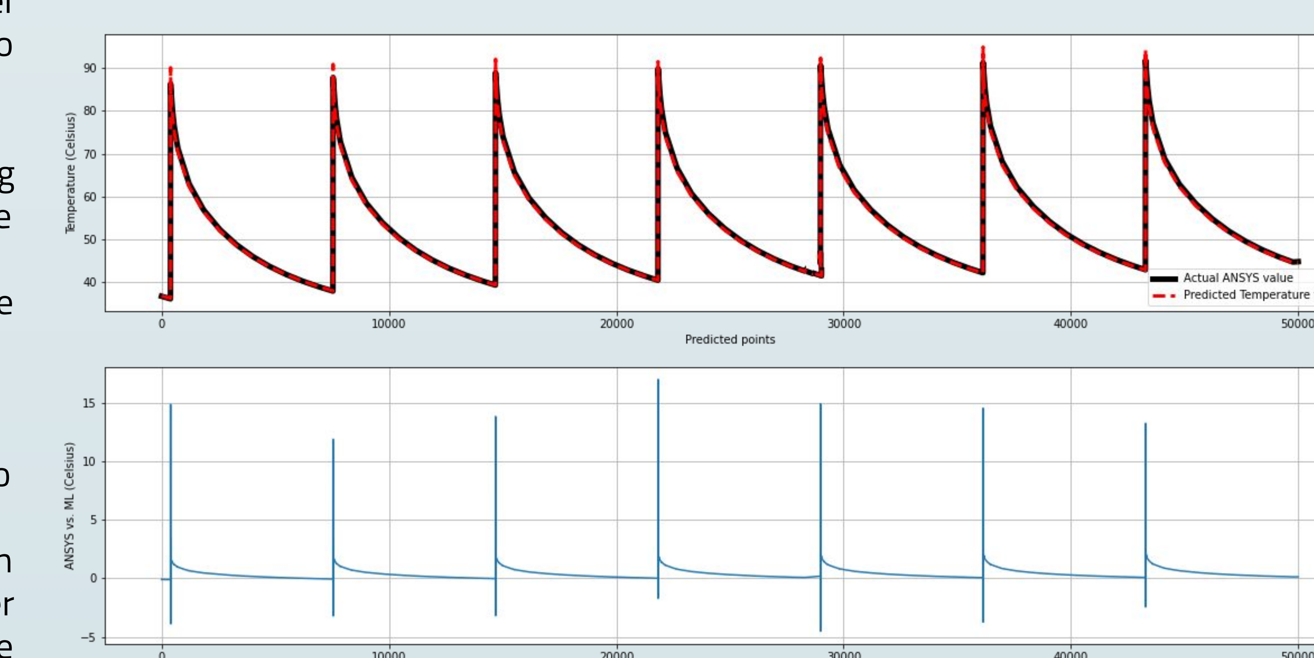

FIG.4 - (Top) Comparison between temperature values calculated in ANSYS and those predicted by the ML-based method. (Bottom) Temperature difference between the ANSYS and the ML-results.