MODELIZATION OF AN INJECTOR WITH MACHINE LEARNING

M. Debongnie[†,] Accelerator and Cryogenic Systems, Orsay, France and Laboratoire de Physique
Subatomique et de Cosmologie, Université Grenoble-Alpes, CNRS/IN2P3, Grenoble, France
F. Bouly, M. Baylac, Laboratoire de Physique Subatomique et de Cosmologie, Université
Grenoble-Alpes, CNRS/IN2P3, Grenoble, France
T. Junquera, Accelerator and Cryogenic Systems, Orsay, France
N. Chauvin, D. Uriot, CEA Saclay/DRF/IRFU, Gif-sur-Yvette, France
A. Gatera, SCK•CEN, Mol, Belgium

Abstract

Modern particle accelerator projects, such as the accelerator for the Multi-purpose hYbrid Research Reactor for High-tech Application (MYRRHA) project driven by the SCK*CEN in Belgium, have very high stability and/or reliability requirements. This means that new strategies for the control systems have to be developed. For that, having faster beam dynamics simulation could prove to be helpful. In this paper, we report the training of neural networks to model key properties of the beam in the MYRRHA injector as well as in IPHI ("Injecteur de Proton à Haute Intensité"). The trained models are shown to be able to reproduce the general behaviours of the machines while requiring a very low computation time.

INTRODUCTION

Modern particle accelerator projects, such as the accelerator for the Multi-purpose hYbrid Research Reactor for High-tech Application (MYRRHA) project driven by the SCK*CEN in Belgium [1], have very high stability and/or reliability requirements. As an ADS demonstrator, the MYRRHA project requires an accelerator able to function with less than 10 beam trips longer than 3 seconds over an operation cycle of 3 months. The consolidated design of this ADS-type proton accelerator is based on a linac solution.) cavities. It is composed of a low energy (normal conducting) injector where a 30 keV beam is transported through the Low Energy Beam Transport line (LEBT) [2] and matched to a 176 MHz 4-rod RFQ [3]. The 1.5 MeV bunched beam at the RFQ output is then accelerated up to 16.6 MeV by CH-cavities [4]. Then the beam is injected into a the main superconducting linac, composed of independently powered superconducting cavities [5] to be accelerated to 600 MeV [6].

To meet the reliability requirements, it is necessary to optimize or develop new methods for the accelerator control systems: to minimise beam losses by achieving fine tuning of the injector, but also to quickly calculate linac settings when a failure compensation has to be applied [7]. One of the difficulties lies in the relatively long computation time of current beam dynamics codes. In this context, the very low computation time of neural network is of great attraction. However, a neural network has to be

---

† mathieu.debongnie@lpsc.in2p3.fr

trained in order to be of any use. The training of a beam dynamic predictor uses a large dataset (experimental or simulated) that represents the dynamics over the parameter space of interest. Therefore, choosing the right training dataset is crucial for the quality of the neural network predictions. In this work, a study on the sampling choice for the training data is performed to train a neural network to predict the characteristics of a beam through proton linac injector (i.e. a LEBT and RFQ). We show and discuss the results obtained on training data set to model the IPHI ("Injecteur de Proton à Haute Intensité") [7] and MYRRHA injectors transmission

THE MYRRHA & IPHI INJECTORS

This work covers injectors with similar designs from two projects: IPHI and MYRRHA. The interest in working come from two points: the first is that the MYRRHA LEBT was not operational at the time this work started and the second is the interests manifested by the IPHI team to optimize the transport in their line. In both cases, a proton beam is extracted from an ion source into a LEBT section. The role of the LEBTs is to shape de beam and drive it into a RFQ, first acceleration and bunching element. To do so, the LEBTs are equipped with two solenoids to focus the beam and four steerers to direct it (see Fig. 1).
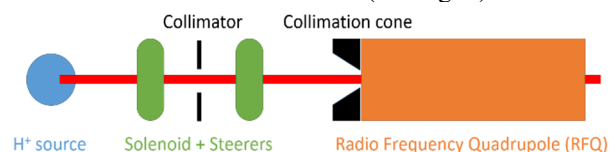

Figure 1: LEBT architecture.

MYRRHA

This injector is designed to provide a 4 mA proton beam with CW operation at the RFQ output. The protons are extracted from the source at 30 keV. In the LEBT, the collimator consists of 4 copper plates that can be moved independently from each other to intercept part of the beam. Note that the RFQ of the MYRRHA injector is currently under commissioning at SCK•CEN (in Louvain-L-N) and thus has not yet been assembled to the LEBT. Therefore, the neural network model was trained using the beam current measured in a faraday cup placed after the collimation cone. The line is equipped with two Allison scanners and two Faraday cups, the firsts of each are

MC5: Beam Dynamics and EM Fields

D11 Code Developments and Simulation Techniques

between the solenoids and the seconds of each are after the collimation cone (see Fig. 2).
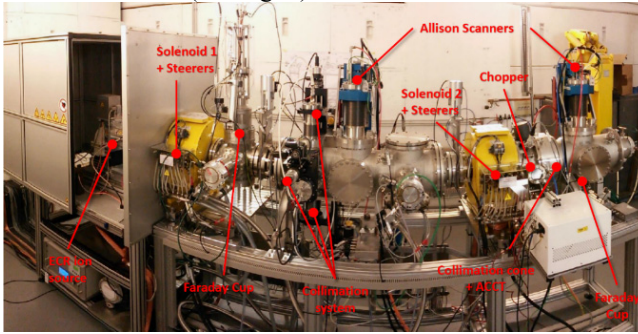

Figure 2: The MYRRHA LEBT [2].

IPHI

This injector has a 65 mA peak current at the RFQ output with a proton beam in pulsed operation (2 ms, 10Hz). The 352 MHz RFQ accelerates the particles from 95 keV up to 3 MeV. The intensity of the beam injected into the RFQ is controlled using an iris between the two solenoids.

NEURAL NETWORKS TRAINING

The neural networks were trained following a Supervised Learning approach. The cost function to minimize is the Root Mean Squared Error (RMSE) of the network over a training dataset, i.e.: the difference between the calculated value by the model and the measured value. The minimization process is done using the stochastic gradient descent method with an initial learning rate of 0.1 that decreases down to 0.001 when the performance of the network does not improve over 5 epochs. An epoch is defined as training the network over 1000 steps with a batch size of 128. At the end of every epoch, the progress of the training is evaluated using a validation dataset. Then, every 10 epochs, the model performance is evaluated over a test dataset.

DATASETS GENERATION

For both machines, the experimental plans followed a straightforward approach: multiple scans on the applied currents in the solenoids and the steerers for different collimator positions are performed while the beam current is measured at the end of the LEBT and, in the case of IPHI, after the RFQ.

MYRRHA

The beam current was measured after the collimation cone with a Faraday cup. The value recorded for the beam current is the average over 200 measurements at a rate of 2 kHz. The scans were separated per type of element, solenoids or steerers. The applied currents in both solenoids ranged from 50 to 110 A and were scanned regularly with a step of 2 A. Therefore, each scan consists of 961 points. 19 scans were performed with different collimator positions. Only the steerers installed in the second solenoid were scanned with currents applied from -3 to 3 A with a step of 0.5 A. Each scan counts 169 points

and 6 scans were performed. In total, a bit more than 19000 configurations were measured and used in the dataset.

IPHI

The beam current was measured at the end of the LEBT with a DC Current Transformer and with an AC Current Transformer just after the RFQ. The measured current was averaged over a minimum of 5 successful pulses. The applied current in the first solenoid was scanned from 50 to 120 A with a step of 2 A. For the second one, the applied current ranged from 145 to 185 A with a step of 2 A. 13 scans were performed with 756 points each. Once again, only the steerers in the second solenoid were scanned. The applied current ranged from -0.5 to 0.5 A with a step of 0.1 A. 2 scans were done however the RFQ suffered from breakdowns and have not been used yet. The full dataset counts slightly less than 9900 points.

In any case, the full datasets are then randomly divided in three: the training dataset ($\sim$60 %), the validation dataset ($\sim$ 20%) and the test dataset ($\sim$ 20%).

NEURAL NETWORK MODELS

Inputs and Outputs: MYRRHA Injector Model

The neural network has 13 inputs: 2 for the applied currents in the solenoids, 4 for the applied currents in the steerers, 4 for the position of the collimator slits and 3 for the pressures measurements. In this case, there is only 1 output as the objective of the neural network is to model the beam current at the end of the LEBT with regard to its configuration.

Inputs and Outputs: IPHI Injector Model

Here the network only counts 3 inputs: 2 for the applied currents in the solenoids and 1 for the position of the iris. The values to model are the beam current after the RFQ as well as the transmission of the RFQ estimated by dividing the current measured after the RFQ by the current measured at the end of the LEBT. Therefore, the network has 2 outputs.

Neural Network Core

The core of the neural network models is identical for the MYRRHA and IPHI injectors. The core of the network is made with 3 fully connected hidden layers (see Fig. 3) with 64 neurons each. The activation function of the hidden layers is the Rectified Linear Unit function. The initialization of the weight follows the He initialization method [8].
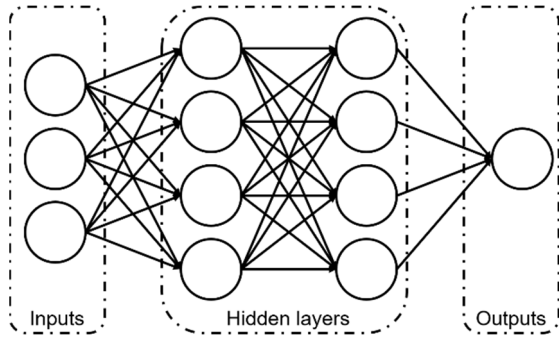
Figure 3: General structure of a fully connected neural network.

RESULTS

The trained models performances were evaluated using the RMSE over the different datasets and by comparison between the experimental data and the model outputs. We here present on Figure 4 one result example obtained on the IPHI injector model.
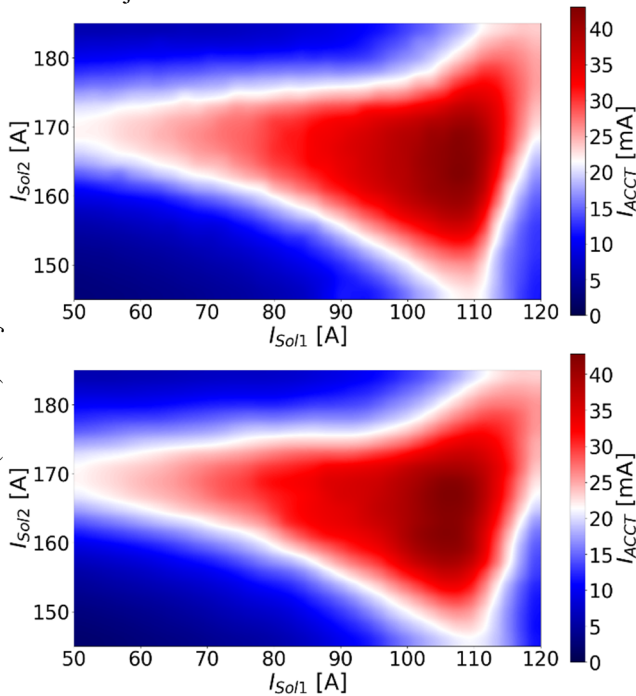

Figure 4: Evolution of the beam current after the RFQ with the current applied to the solenoids on IPHI: experiment (top) and model (bottom).

The comparison done here is between the beam current experimentally measured on IPHI during a solenoid scan (top) and the beam current simulated with the neural network (bottom). Even though the neural network was trained on only 60 % of the points in the scan, it is able to reproduce the behaviour of the measured beam current over the whole scan.

The RMSE of the IPHI injector model on the test dataset is 0.81 mA for the beam current and 1.65 % for the RFQ transmission. The MYRRHA LEBT model has a RMSE equal to 0.45 mA for the beam current on its test dataset. The RMSEs over the different datasets are given in Table

1. The training dataset (60 % of the data) is used to optimize the parameters of the neural network, the validation and test datasets (20 % of the data each) are used to verify the progress of the training and avoid overfitting and the combined datasets (100 % of the data) regroups these three datasets.

Table 1: RMSE over the Different Datasets

	MYRRHA	IPHI	
Dataset	**RMSE on Beam cur. [mA]**	**RMSE on Beam cur. [mA]**	**RMSE on RFQ trans. [%]**
Training	0.46	0.66	1.25
Validation	0.44	0.79	1.62
Test	0.45	0.81	1.65
Combined	0.46	0.72	1.42

These results show that a neural network can be trained to model important beam properties governed by complex physics. Furthermore, the computation time of the trained model is very low at ~10 µs per configuration.

CONCLUSION & PROSPECTS

In this study, we have trained multiple neural networks to model key characteristics of proton beams in two different injectors. The resulting models are able to reproduce the general behaviour of the beam current and the RFQ transmission over a wide range of possible configurations of the injectors. This and the very low computation time of the trained model make neural network attractive to develop new control strategies. A straightforward approach would be to use standard optimization algorithms on the trained model to determine an approximate configuration to obtain desired beam properties. Also, the trained models will be used to train a neural network controller using reinforcement learning. In this case, the neural network controller would learn to behave in a similar way to a human operator by interacting with the trained model. This approach will be explored soon for the high-energy part of the MYRRHA linac with the aim to develop a solution for the fast reconfiguration needed for the fault tolerant strategy.

ACKNOWLEDGMENT

REFERENCES

[1] MYRRHA, https://myrrha.be/.

[2] F. Bouly *et al*., "Commissioning of the MYRRHA Low Energy Beam Transport Line and Space Charge Compensation Experiments", in *Proc 8th Int. Particle*

Accelerator Conf. (IPAC'17), Copenhagen, Denmark, May 2017, pp. 1226-1229,
`doi:10.18429/JACoW-IPAC2017-TUOBA2`

[3] K. Kümpel *et al.*, "Measurements of the MYRRHA-RFQ at the IAP Frankfurt", in *Proc. 9th Int. Particle Accelerator Conf. (IPAC'18)*, Vancouver, Canada, Apr.-May 2018, pp. 949-951, `doi:10.18429/JACoW-IPAC2018-TUPAF090`

[4] K. Kümpel, S. Lamprecht, N. F. Petry, and H. Podlech, "Tests and Conditioning of the MYRRHA CH Cavities 1 and 2", presented at the 10th Int. Particle Accelerator Conf. (IPAC'19), Melbourne, Australia, May 2019, paper MOPTS022, this conference.

[5] F. Bouly, M. A. Baylac, D. Uriot, and A. Gatera, "Superconducting Linac Design Upgrade in View of the 100 MeV MYRRHA Phase I", presented at the 10th Int. Particle Accelerator Conf. (IPAC'19), Melbourne, Australia, May 2019, paper MOPTS003, this conference.

[6] F. Bouly *et al.*, "Fault Tolerance and Consequences in the MYRRHA Superconducting Linac", in *Proc. 27th Linear Accelerator Conf. (LINAC'14)*, Geneva, Switzerland, Aug.-Sep. 2014, paper MOPP103, pp. 297-299.

[7] F. Senee *et al.*, "Increase of IPHI Beam Power at CEA Saclay", in *Proc. 9th Int. Particle Accelerator Conf. (IPAC'18)*, Vancouver, Canada, Apr.-May 2018, pp. 694-696, `doi:10.18429/JACoW-IPAC2018-TUPAF016`

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, "Delving Deep into Rectifiers: Surpassing Human-Level Performance onf ImageNet Classification", in *IEEE International Conference on Computer Vision (ICCV)*, 2015, pp. 1026-1034.