14th International Particle Accelerator Conference,Venice, Italy JACoW Publishing
ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA094

MODEL OF A DYNAMIC ORBIT CORRECTION SYSTEM BASED ON NEURAL NETWORK IN CLS

S. Saadat[1]* and M. J. Boland[1,2],
[1]Canadian Light Source, Saskatoon, Canada
[2]University of Saskatchewan, Department of Physics and Engineering Physics, Saskatoon, Canada

Abstract

In CLS, Deep Learning was applied to make a dynamic model for the Orbit Correction System (OCS). The OCS consists of 48 sets of BPMs BERGOZ (96 data sheets with 900 Hz recording) that measure the beam position and use the SVD matrix to calculate the strength of the orbit correctors (48 sets of Orbit Correctors 'OC'). The Neural Network was built, trained, and tested using 96 BPM signals. Five layers of the network (Input Layer, Three Hidden Layers, and Output Layer) provide the time evolution of OC's signals (18 Hz), which can be achieved with high accuracy (Mean Square Error = 10^{-7}). The results are based on data collected during all challenging situations of the CLS storage ring's current beam position. An Arduino Board was used to test this methodology in real time, and the time of operation was within the range of system timing (30 - 40 microseconds).

INTRODUCTION

CLS (Canadian Light Source) is a synchrotron light source. There are 12 sections in the storage ring, which runs at 2.9 GeV. A perturbation of the electron position in the closed orbit leads to a decrease in beam lifetime and fluctuations in light at the beamlines. These perturbations are corrected by the Orbit Correction System (OCS). The orbit correction system of the CLS includes a computer running Matlab, four Versa Module Eurocards (VMEs), each of which corresponds to three sections of the storage ring, and a Real-Time Executive for Multiprocessor System (RTEMS) (Figure 1). The 96 Bergoz Beam Position Monitors (BPMs)

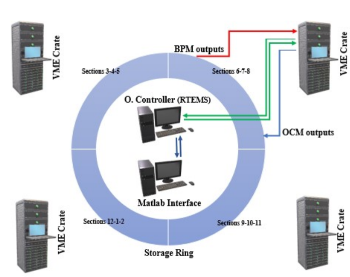

Figure 1: Schematic of orbit feedback system in CLS.

are digitized by the Analog to Digital Converter (ADC) ICS-110BL at 50Hz, and finally, the 96 correctors feed at 18Hz [1].

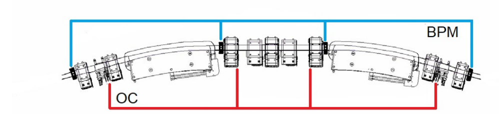

Figure 2: BPMs and OCMs location in each cell for CLS.

In 2000, a Motorola single-board computer was installed as the first real-time controller [2]. The old orbit correction system was upgraded to the present OCS in 2008 [3]. A fast orbit correction system was designed and tested in CLS in 2009. The new system has a tunable rate between 20 Hz and 100 Hz [4]. The CLS Matlab application (CLSORB) has been developed to modify correction rates to 45 Hz and 18 Hz for correctors [5]. Hardware and software orbit control systems were developed until the RMS deviation of beam motion was less than one micrometer in the X and Y directions.

Every cell contains four horizontal and vertical beam position monitors (BPMs), and 4 orbit corrector magnets (OCMs), where 2 slow correctors are located between the bendings, and 2 fast correctors are located on either side of the dipoles (Figure 2) .

The Singular Value Decomposition (SVD) is provided by the Matlab interface. The SVD can be calculated at all BPMs, by adjusting the strength of each OCM by a small amount [6]. As the main component of the orbit correction system, this response matrix plays a crucial role. In this research, we replace the SVD function with a neural network algorithm as the orbit correction system's brain.

Dynamic learning capabilities of neural networks can reduce unneeded fluctuations and resonances in beam position and control chaotic behavior. We are now in the process of developing a dynamic orbit correction controller for the CLS.

NEURAL NETWORK MODEL

Artificial neural networks (ANNs) emulate biological neural networks, which are able to store and recall large amounts of information and exhibit high levels of solving problems. Using elementary operations, these mathematical models can quickly solve stochastic, nonlinear, and complex problems. The creation of an ANN requires many parameters, known as network architectures. Number of Inputs p_i (neurons or nodes), Number of Layers a^i , Biases b^i_j, Weights w^i, and Activation functions f^i are shown in the Figure 3 [7].

* shervin.saadat@lightsource.ca

ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA094

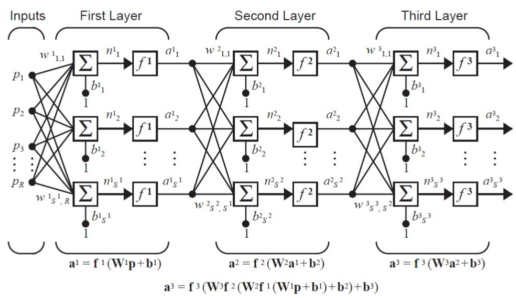

Figure 3: A three layers ANN with Number of Inputs p_i, Number of Layers a^i, Biases b^i_j, Weights w^i, and Activation functions f^i.

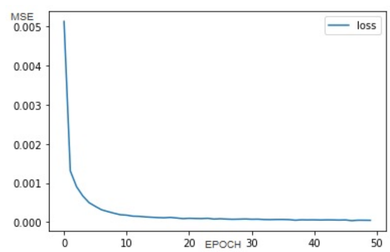

Figure 4: Loss behaviour of MSE for 50 epochs.

The next sections discuss neural network architecture and parameters for orbit correction system model of the CLS.

Network Architecture

In this case, the first layer should consist of 96 neurons for 96 BPMs data, because the number of neurons depends on the inputs, in addition, there are 96 outputs for 96 OCMs. The same number of inputs and outputs prevent us from expanding nodes in hidden layers, so we select 96 nodes per hidden layer. Several hidden layers(1, 2, 3) are selected and tested to find the best result. Additionally, increasing the hidden layers can increase the calculation time, so in this case, the maximum number of layers selected is 3 hidden layers, which is a famous NN. Finally, the NN consists of 96 nodes for input, hidden layers, and output, as well as three hidden layers [8].

In order to create this architecture, first, a code was created by python and tested. In spite of the excellent results with about $2.1 * 10^{-6}$ Mean Square Error (MSE), the learning time was outside of the acceptable range. Modeling of the TensorFlow-Keras library [9] was performed, MSE was around 10^{-7}, and the calculation time was shorter, therefore, we continued by using this library. Using a random weight distribution, the mean square error is reduced rapidly in the TensorFlow model, and after several iterations (EPOCH) has reached an acceptable level. In Figure 4, TensorFlow-Keras shows the loss behavior of MSE for fifty epochs.

Network Parameters

As one of the most important issues in NN, the preparation of data for learning is an essential part of the process. Inputs and outputs in the network should be between 1 and -1, while BPMs are between $+10^3$ and -10^3 , OCMs are distributed between $+10^6$ and -10^6. BPMs and OCMs are sampled at 1 kHz, and two huge tables(Inputs and outputs) with 1000 rows and 96 columns are available at one second, which must be normalized. By dividing the absolute value of the row maximum value for each row, normalization can be achieved. A discussion about other faster normalization techniques will follow in the conclusion.

There are many activation functions that can be used in NN modeling, Sigmoid is the most famous, which changes between 0 and 1 [10]. The Hyperbolic Tangent ($Tanh$) was used because the input data changed between -1 and 1. By comparing these two activation functions, $Tanh$ found the model faster than Sigmoid and it was predictable.

It is selected that, 70 percent of the database will be used for training and 30 percent for testing.

This step, Learning, involves splitting the saved data into five-minute, twenty-minute, and sixty-minute segments, training the neural network, and finally creating the model. The test mean square error is $(3.152360 * 10^{-7})$ and the train mean square error is $(3.152210 * 10^{-7})$ with 20 epochs. The MSE values of testing and training indicate that the new model is fairly accurate. In the Figure 5, outputs of both the orbit correction system (Green) and NN model (Blue) to OCVs are plotted at the same time, since these outputs are matched perfectly with real data.

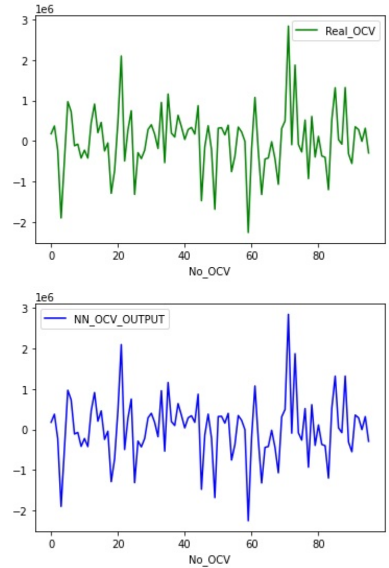

Figure 5: Orbit Correction System outputs for 96 OCVs are plotted in green, and neural network outputs to OCVs are plotted in blue.

REAL-TIME SIMULATION

The CLS orbit correction system receives a data stream with 1 kHz from 96 BPMs, normalizes it to 1, passes it to the NN model, and sends the output data with 1 kHz to OCMs. In a correction system, NN model accuracy is adequate but needs to be improved in terms of timing and modification

ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA094

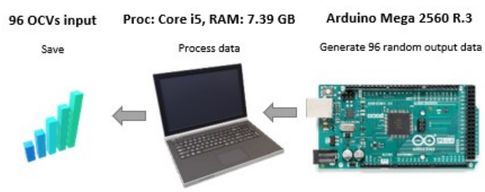

Figure 6: The schematic of the simulator to generate BPMs outputs and OCMs inputs.

based on real-time data. This was accomplished by generating a real-time serial data set as BPMs via a simulation. The Arduino mega 2560 is programmed to generate 96 outputs with compatible frequencies. The data stream is sent to a system with 11th Gen Intel(R) Core(TM) i5-1145G7(2.60-1.50GHz) processor and 7.39 GB RAM sent and processed, then sent to the OCMs (Figure 6). The real system works at 900 Hz for BPMs outputs and 18 Hz for OCMs inputs, The Arduino can produce 900 Hz (Serial 115200) but the existing system could not work less than 50 Hz, Which means the system must read (900*96) data per second and generate (18*96) data per second, but this hardware reads (50*96) data per second and produces (1*96) per second. For this purpose, we have to upgrade the hardware in the future.

Arduino data is streamed to the hardware via the Serial library. BPMs and OCMs are normalized with constant values instead of row-to-row normalizations to decrease calculation time. According to CLS data, BPMs have maximum values of $5 * 10^3$ (MxBPM) and OCMs have maximum values of $5 * 10^6$ (MxOCM). Inputs are divided by MxBPM and outputs are multiplied by MxOCM.

In this method, normalization takes 16 milliseconds, and NN modeling and data preparation for OCMs takes 46 milliseconds, so 60 - 65 milliseconds is close to real system time.

An evaluation of the NN model's long-term ability was conducted, and the new algorithm worked flawlessly for 56 hours.

CONCLUSION

This research is about using TensorFlow to develop the CLS orbit correction system. Learning and operating the system with fast real-time data are its main objectives. Clearly, the error on learning decreases with the time of algorithm training, as seen in Figure 7 where three trainings are shown with 60k, 300k, and 600k data. The average error percentage for the first training is 1.692526%, for the second, 1.061518%, and the last one has 0.91738%. A mean square error of 10^{-7} was found in the model, and real-time data was operated at 65 ms intervals. After one hour of training (3.6M data), the error goes down to $(3.152200 * 10^{-7})$.

In addition, this learning works with two hidden layers, except the calculation time is faster, but the error rate decreases more slowly. Faster calculations are more important for deep learning models than speed rates of error, so two hidden layers are a better architecture.

The real BPMs system sends 900 data per second to OCS, then 18 data passes to OCMs, so we must average 50 inputs before passing them to the algorithm. We tested three methods,

1- Waiting for 50 inputs, then averaging them,

2- Adding 50 data together at the moment, then dividing by 50,

3- Averaging every 50 data at the moment.

The second technique was 13 percent faster than the others, and this method is used for normalization. The system appears to be faster at calculating than saving and reading data.

Using the Arduino simulator, the Dynamic model reads, analyses, and generates OCM outputs very smoothly, showing the ability of the model to function on the actual machine.

Based on all calculations, the results obtained were quite impressive. As a result of this study, it was demonstrated that deep learning is a powerful tool for orbit correction systems in storage rings.

Further applications of deep learning could be found for accelerators, synchrotrons, light sources, and beam lines in the future.

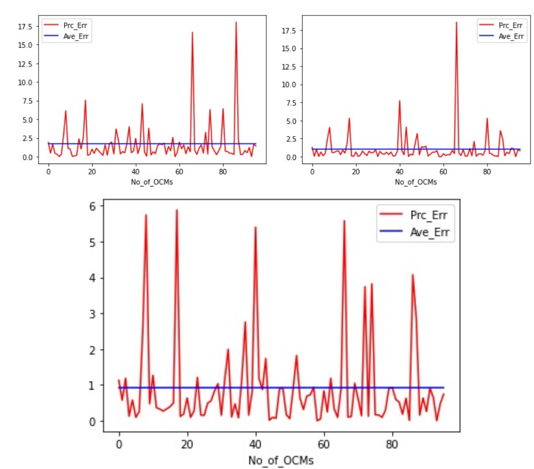

Figure 7: The percent error of OCMs (Red line), and average error (Blue line), with 60k (1.69%), 300k (1.06%) and 600k (0.92%) data training by 20 epochs.

ACKNOWLEDGEMENTS

The authors would like to thank Tonia Batten, Johannes Vogt, Ward Wurtz, Cameron Baribeau, Hamed Shaker, Drew Bertwistle, Mike Bree, and Fredric Le Pimpec, as well as all other AOD members of the CLS operation group.

REFERENCES

[1] T. Summers, D. Chabot, L. O. Dallin, and M. J. Sigrist, "Orbit Improvements at the Canadian Light Source", in *Proc. PAC'09*, Vancouver, Canada, May 2009, paper TU5RFP018, pp. 1129–1131.

ISBN: 978-3-95450-231-8 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2023-WEPA094

[2] L. Dallin, I. Blomqvist, D. Lowe, M. Silzer, and M. de Jong, "The Canadian Light Source", in *Proc. PAC'03*, Portland, OR, USA, May 2003, paper TOPA001, pp. 220-223.

[3] D. Chabot, "Sr1 orbit control design note," *CLS Document*, vol. 5, no. 39.4, 2008.

[4] C. G. Payne and D. Chabot, "Fast Orbit Correction at the Canadian Light Source", in *Proc. PCaPAC'10*, Saskatoon, Canada, Oct. 2010, paper WECOMA02, pp. 9–11.

[5] S. Hu, C. Payne, D. Chabot, D. Maxwell, and L. Dallin, "Global orbit feedback system upgrade at the canadian light source," *Jornal of Physics: Conf. Ser.*, vol. 425, p. 042009, 2013. doi:10.1088/1742-6596/425/4/042009

[6] Jingyi Li, Gongfa Liu, Weimin Li, Baogen Sun, Caozheng Diao, Zuping Liu, "Development of orbit correction system of HLS storage ring", in *Proc. APAC'01*, Beijing, China, Sep. 2001, paper TUP032, pp. 681–683.

[7] M. T. Hagan, H. B. Demuth, and M. Beale, *Neural network design*, Uni. Colorado, 2nd Ed., 2002.

[8] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998. doi:10.1109/5.726791

[9] https://www.tensorflow.org/.

[10] C. Nwankpa,W. Ijomah, A. Gachagan, and S. Marshall, "Activation functions: Comparison of trends in practice and research for deep learning," *arXiv Preprint*, 2018. doi:10.48550/arXiv.1811.03378