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A New Approach For Canadian Light Source Future Orbit Correction System Driven By Neural Network

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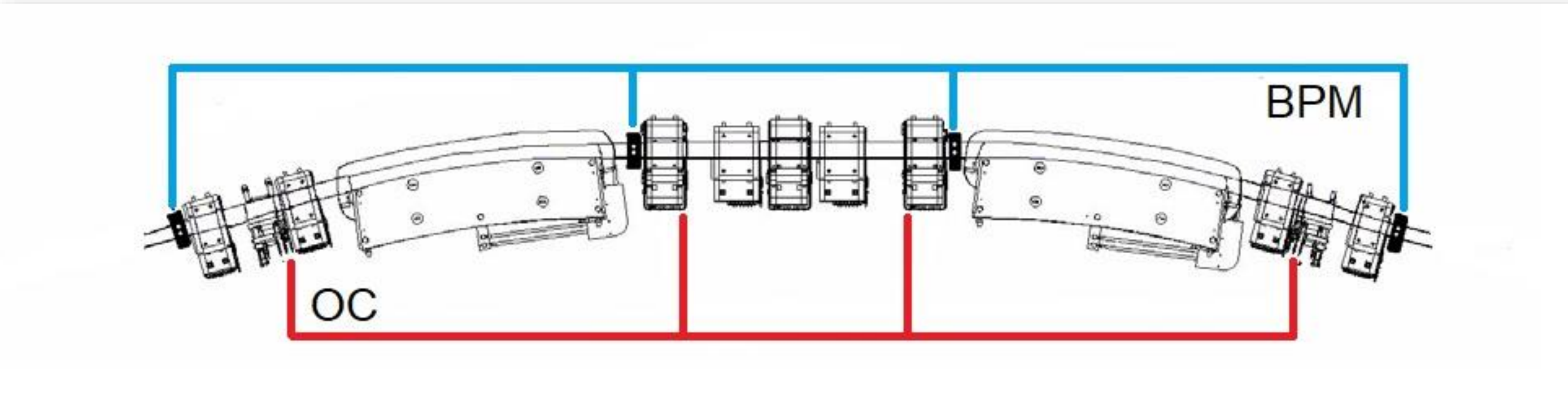
Abstract

The Canadian Light Source (CLS) uses a 48-set orbit correction system (OCS) with BERGOZ beam position monitors (BPM) to track beam positions at 900 Hz. The Inverse Response Matrix (IRM) is employed to optimize beam path using 48 sets of orbit correctors. The study proposes replacing SVD with the neural network algorithm, featuring a 3-layer model with 96 nodes each. The neural network's typical MSE in CLS operations is 10^{-7}. Testing the OCS at 8.0 mA with various challenges showed the new model effectively generated required orbit corrector signals.

Canadian Light Source

CLS (Canadian Light Source) is a synchrotron light source. There are 12 sections in the storage ring, which runs at 2.9 GeV. Every cell contains four horizontal and vertical beam position monitors (BPMs), and 4 orbit corrector magnets (OCMs).

The SVD can be calculated at all BPMs, by adjusting the strength of each OCM.



Neural Network Model

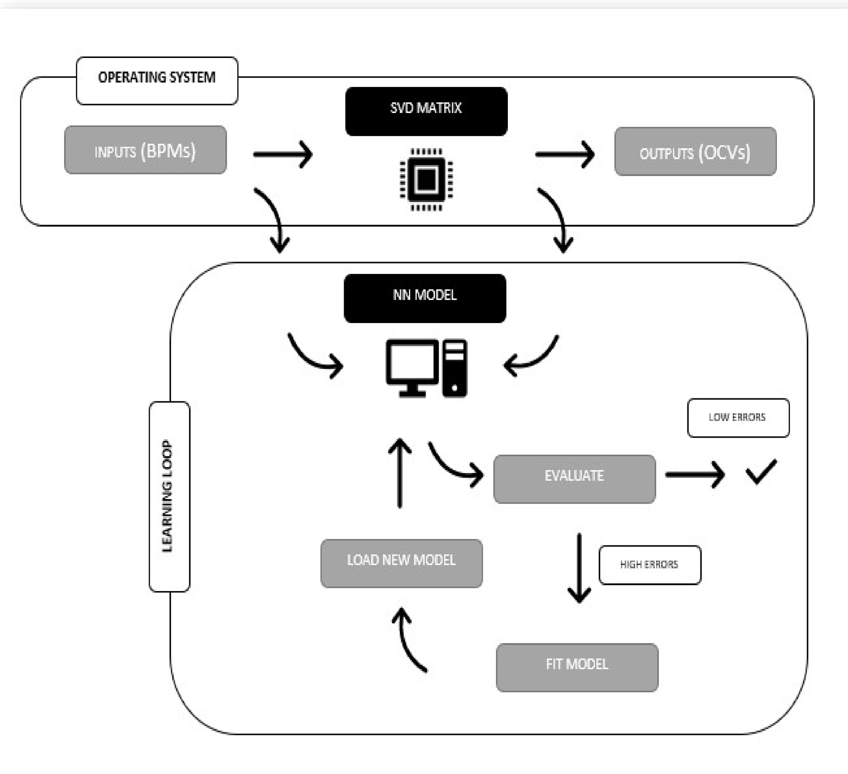
The first layer should consist of 96 neurons for 96 BPMs data, because the number of neurons depends on the inputs, in addition, there are 96 outputs for 96 OCMs.

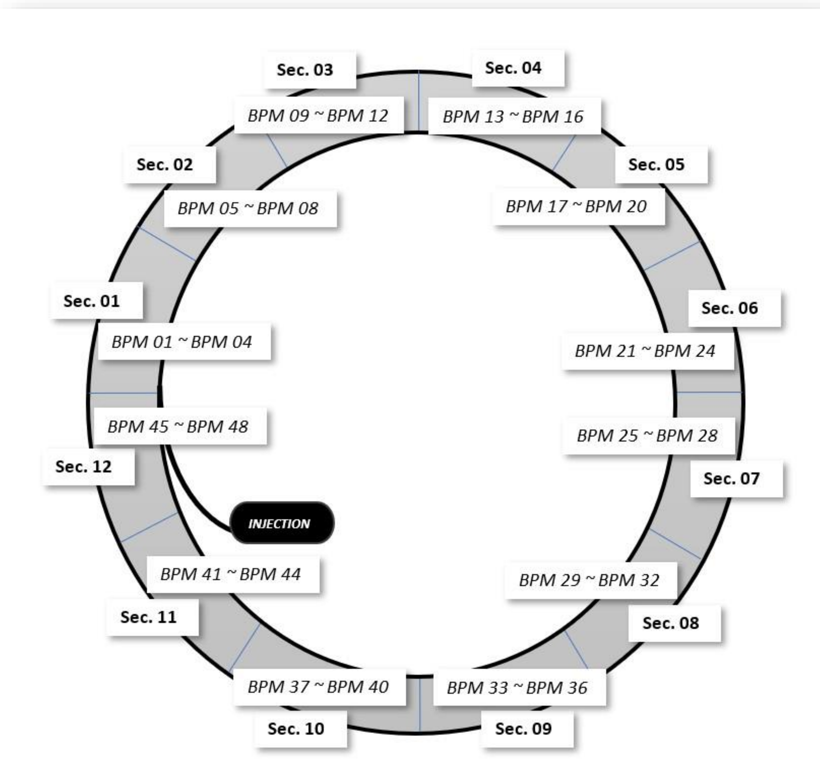
The same number of inputs and outputs prevent us from expanding nodes in hidden layers, so we select 96 nodes per hidden layer. Modeling of the TensorFlow-Keras library was performed, MSE was around 10^{-7}.

The Hyperbolic Tangent ($Tanh$) was used because the input data changed between -1 and 1. 70 percent of the database was used for training and 30 percent for testing and finally the model was created.

The test mean square error is $(3.1524 * 10^{-7})$ and the train mean square error is $(3.1522 * 10^{-7})$ with 20 epochs. The MSE values of testing and training indicate that the new model is fairly accurate.

The initial model demonstrated real-time accuracy on stable data with minimal errors. To accommodate significant beam position changes, the neural network must be versatile, requiring diverse training data. A learning loop is implemented, evaluating new datasets with the initial model, updating it as needed for improved accuracy based on error thresholds, ensuring the best-performing model replaces the previous one.



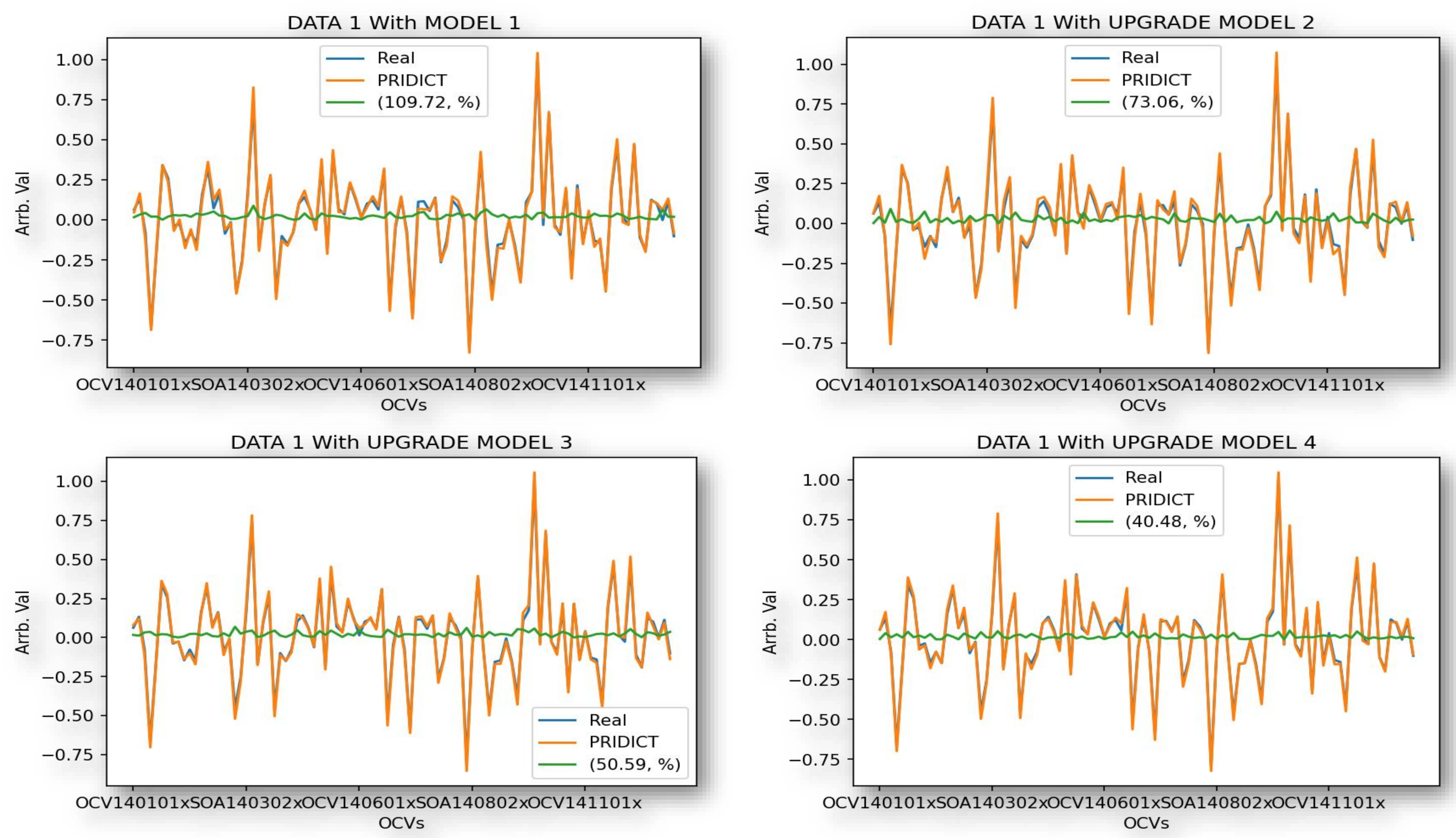


Experiments and Results

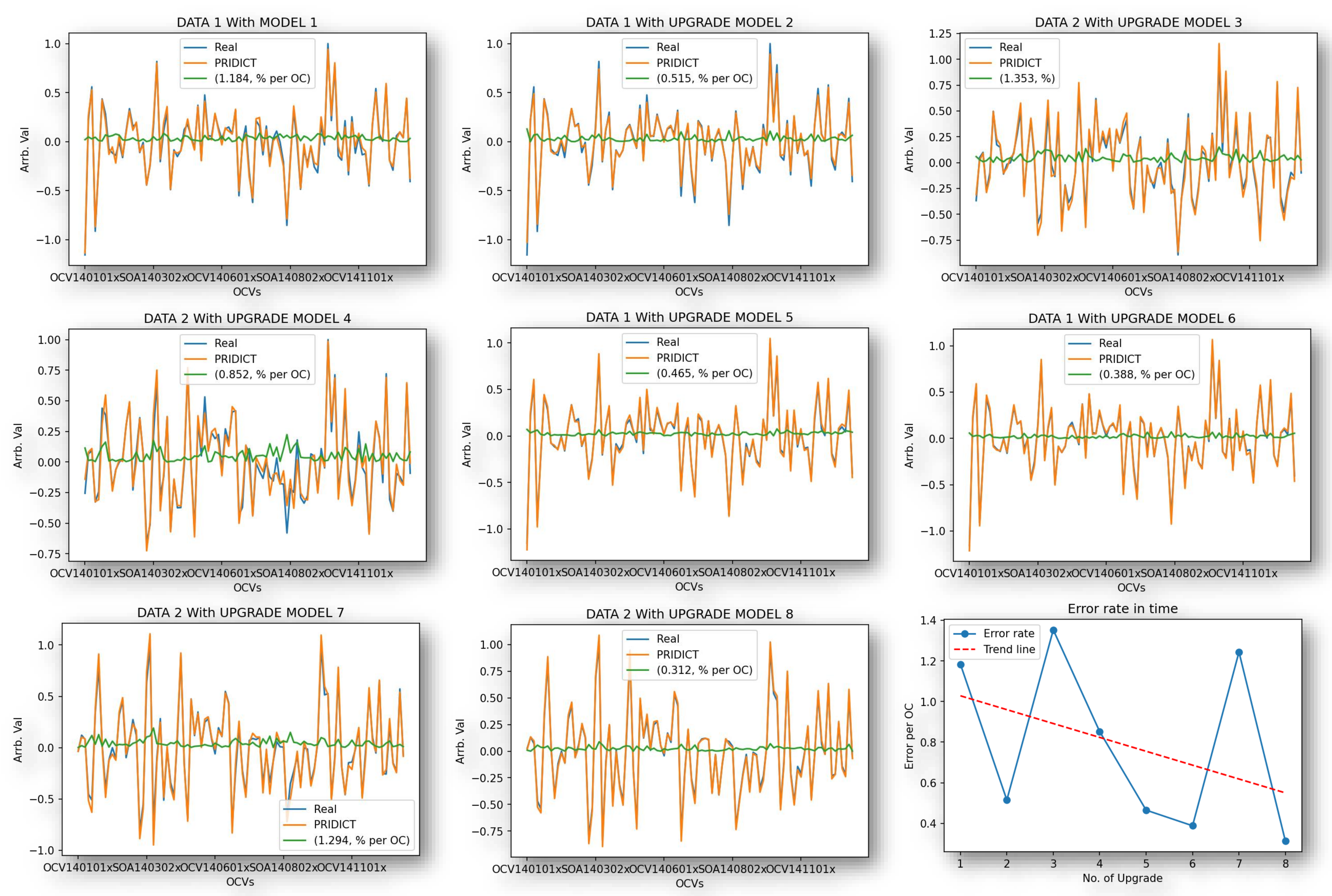
In the first scenario, when the system is functioning normally, we conducted the learning loop four times. During the first phase, we developed the model, while the second to fourth phases involved updating the model.

In the second scenario, the beam position is expected to undergo a sudden change, presenting a challenging situation for the OCS. We aim to investigate whether this loop can update a model with memorized coefficients, furthermore, we will calculate the error that arises during this process*.

* We introduced a metric called Accumulated Error (AE), which represents the sum of errors across all OCs.



In this experiment, the BPM's values in different sections of the SR were changed by adjusting the reference (offset) to create a desired beam position situation(+1 and -1 mm) for the OC system. The system was tested at a beam current of 8.0 mA.



Conclusion

Two conditions of the NN model's effectiveness were investigated, a stable mode and a complex mode. The results for the stable mode demonstrate that error rates decrease over time, from 1.1% per OC in the first experiment to 0.42% per OC after four steps. While this result was expected, it provides further confirmation of the effective operation of the deep learning loops in the NN model, which successfully reduces error rates over time in the stable mode condition. The results of the second scenario are less clear than those of the stable mode upgrade, although they do exhibit a decreasing trend in error rates despite some fluctuation(Last Picture). There shows a decreasing trend in prediction errors for a specific data set(upgrades1 and 2), but the deep learning model is unable to generalize its performance to new data sets(upgrade 3) without further training. However, next step training result in reduced errors on new data sets(upgrades 4, 5). This cycle continues, and the errors decrease smoothly over time.

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