ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-WEPAL030

DEEP LEARNING BASED PREDICTIVE CONTROL FOR RFT-30 CYCLOTRON

Y. B. Kong, E. J. Lee, H. S. Song, M. G. Hur†, J. H. Park, S. D. Yang, KAERI, Jeongeup, Korea

Abstract

Successful construction of the control system is an important problem in the accelerator. The control behavior still relies on the human operators and the operators should directly manipulate the devices to control the accelerator system. To operate the accelerator well, the human operators should carefully manipulate the control parameters. If the control does not function properly, it becomes difficult to handle the accelerator and cannot perform the accurate operations for the control. In this work, we propose a deep learning based model predictive control approach for solving the nonlinear control problem of the accelerator. The proposed approach constructs the predictive model of the accelerator using the deep neural network (DNN). In the control design stage, the model predictive control (MPC) finds the optimal control inputs by solving the optimization problem. To analyze the performance of the proposed approach, we applied the proposed approach into the RFT-30 cyclotron.

INTRODUCTION

Recently, particle accelerators become more promising devices for industrial, environmental, and medical applications. Easy operation and minimum maintenance are indispensable parts for the convenient use of the accelerator. In particular, a control problem is an important and critical issue for easy and effective operation of the accelerator. If the control does not function properly, the accelerator may become difficult to handle and cannot perform the accurate operations.

In this work, we propose a deep neural network (DNN) based model predictive control (MPC) approach for the RFT-30 cyclotron. To control highly non-linear and time-varying system, we applied the deep learning model with deep neural network (DNN) into the control approach. The proposed approach constructs the beamline model based on the deep belief network (DBN) [1]. Based on the DBN-DNN model, the predictive controller finds the optimal control parameters of the beamline for the desired output. We analyzed the performance of the proposed approach for the RFT-30 cyclotron beamline system. The proposed DNN MPC approach can minimize the beam tuning time and enables effective beam control. Moreover, combined with other control techniques, the proposed approach enables beam auto-tuning and control automation.

DEEP BELIEF NETWORK DEEP NEURAL NETWORK (DBN-DNN) ARCHITECTURE

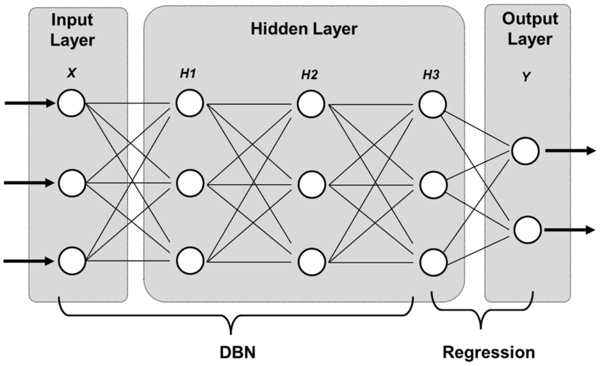

Figure 1: The overview of DBN-DNN structure.

Hinton et al proposed the deep belief networks (DBPs) for deep learning [1]. Figure 1 shows the basic overview of the DBN-DNN structure. The DBN learning is composed of pre-training procedure and fine tuning procedure. The pre-training is to decide the weight between the layers to train the model accurately before the main training. After pre-training procedure, the proposed approach performs the fine tuning with the error back propagation algorithm.

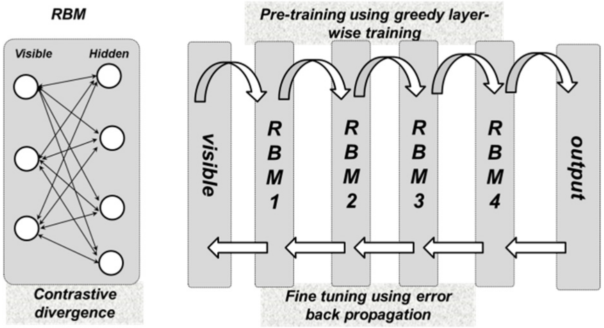

Figure 2: The RBM structure and training procedure.

Figure 2 shows the RBM structure and the learning procedure. The pre-training procedure trains the model using the restricted boltzman machine (RBM). The pre-training procedure is an unsupervised learning to find the optimum weights (W) between the input layer (visible layer) and the hidden layer. The learning is to find the weights W which maximize the log likelihood based on the energy function and it can be written as

---

† hur09@kaeri.re.kr

ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-WEPAL030

$$p(v,h) = \frac{e^{-E(v,h)}}{Z}$$

$$E(v,h) = -h^T W v - c^T v - b^T h \qquad (1)$$

Each weight is updated using the Contrastive divergence and Gibbs-sampling [1]. After the pre-training procedure, the DBN-DNN performs the fine tuning using the error back-propagation algorithm. This process is similar to the multilayer perceptron of the artificial neural network. The fine-tuning procedure updates the weights W to minimize the error between the output layer value and the output data. The direction of the fine tuning is from the output layer to the visible layer.

DNN BASED MPC FOR RFT-30 CYCLOTRON

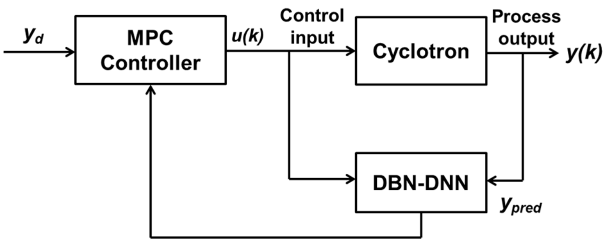

Figure 3: A DNN-DBN based MPC approach.

In this work, we propose a DNN based MPC approach for RFT-30 cyclotron. Figure 3 shows the basic architecture of the proposed DNN-MPC approach. The DNN-MPC is composed of the DNN and MPC blocks. The DNN block predicts the system output using the control input. The MPC block finds the optimum input with the desired output and the predictive output, and it can be written as following optimization problem:

Minimize

$$\sum_{i=1}^{Np} (y_d - \hat{y}(k+i-1))^2 - \lambda \sum_{j=1}^{Nu} (u(k) - u(k+j-1))^2 \qquad (3)$$

where N_p is the prediction horizon, y_d is the reference trajectory, N_p is the control horizon, u is the control input, and λ is weighting factor. As shown in Fig. 4, the MPC approach solves the optimization problem using the predictive output and the future control input.

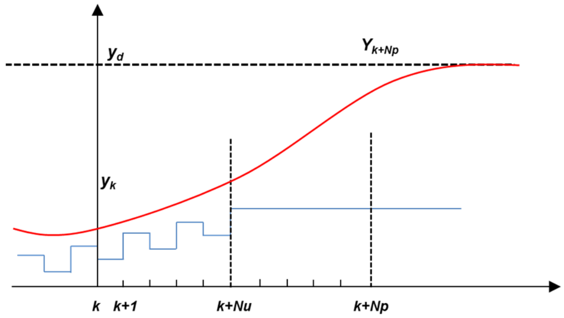

Figure 4: Model predictive control approach.

The DDB-DNN block is a system identification block. Figure 5 shows the DNN training procedure. First, the DNN structure is created with the input, hidden, and output layers. Next, the RBM layers are pre-trained using the contrastive divergence and Gibbs sampling. Finally, the fine tuning process based on the error back propagation algorithm optimizes the DNN block.

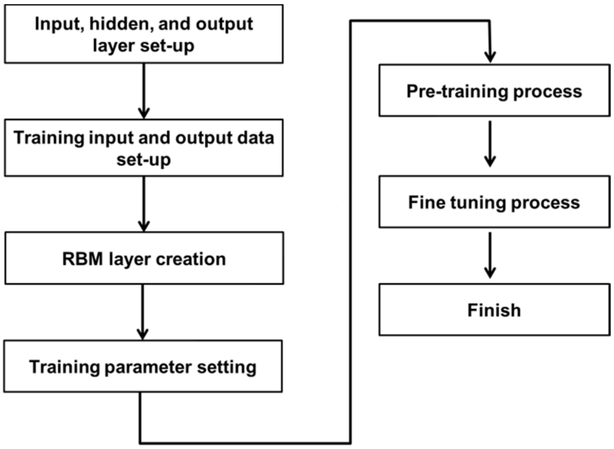

Figure 5: Overview of the DNN-DBN training procedure.

SIMULATION RESULTS

To analyze the performance of the proposed NN MPC approach, we performed the evaluations based on the RFT-30 cyclotron beamline system. The RFT-30 cyclotron installed at KAERI is 30 MeV cyclotron used for RI production and fundamental researches. Figure 6 shows the cyclotron beamline system. The beamline is composed of drum collimator (DC), steering magnet (ST), quadrupole magnet (QA, QB, QC), quadrant (QD), and vault/target faradaycup (FC). In order to transmit the proton beam safely into the beamline target, the operator should carefully perform the beam tuning using the beamline components. The cyclotron operator receives the feedback data from the beam diagnostic devices and performs the beam tuning by adjusting the magnets.

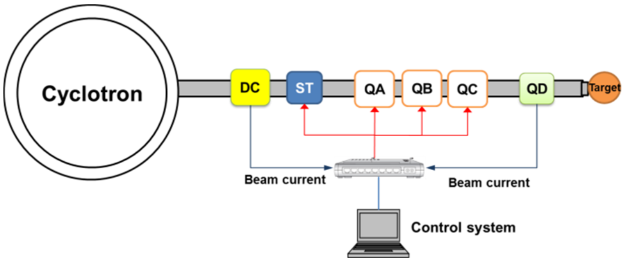

Figure 6: The DBN-DNN beamline model.

We constructed the DBN-DNN model for the RFT-30 cyclotron using the beamline simulation. The simulation is performed through the simple accelerator modeling in matlab (SAMM) [3]. After the beamline simulation, the input and the output data are used for the DNN training.

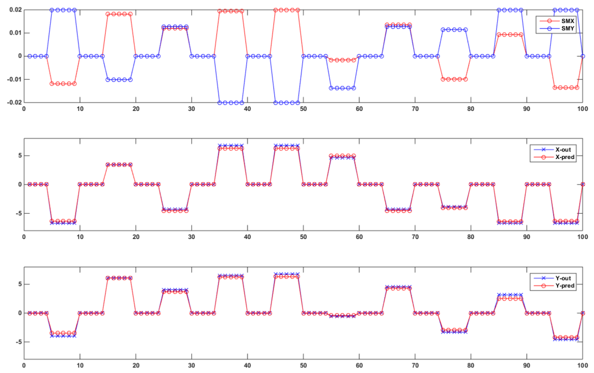

Figure 7: Performance results of the DNN prediction.

Based on the training data, we constructed the beamline model using the DBN-DNN code [4]. We randomly generated the input parameters for the steering magnets and estimated the beam position with the SAMM simulation. We changed the input every 5 time steps and compared the simulation output with the predictive DNN output. As shown in Fig. 7, the predictive DNN output is close to the beamline simulation output.

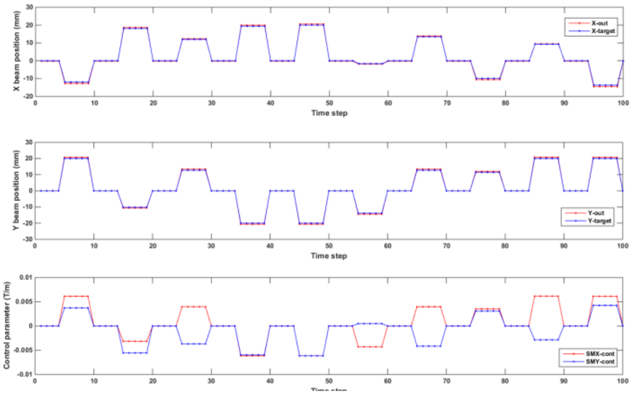

Figure 8: Performance results of the DNN-MPC approach.

Next, we performed the evaluations for the proposed DNN-MPC approach. The proposed MPC approach finds the input parameters for the specific reference trajectory based on the DNN predictive model. The predictive controller finds the parameters by using the quasi-Newton optimization algorithm. As shown in Fig. 8, the beamline output for the input parameters is close to the target output. The performance results show that the proposed DNN-MPC approach can control the beamline system accurately.

CONCLUSIONS

The beamline tuning is an important problem in the accelerator system, but it is a difficult task and a time consuming work for the human operators. In this work, we proposed a DNN based MPC approach for the RFT-30 cyclotron. The proposed approach enables the human operators to be easy beamline tuning and provides the operators with reducing the time for the accelerator operation. In the future, we plan to apply the proposed DNN MPC approach into the control system of the RFT-30 cyclotron.

REFERENCES

[1] G. Hinton *et al.*, “A Fast Learning algorithm for Deep Belief Nets”, *Neural Comput.*, vol. 18. No. 7, pp. 2133-2136, 2006.

[2] D. Soloway *et al.*, “Neural Generalized Predictive Control”, *IEEE International Symposium on Intelligent Control*, Dearbon, USA, Sept. 1996, pp. 277-282.

[3] ***http://pcwww.liv.ac.kr/~awolski/main_links_computercodes.htm.***

[4] M. Tanaka *et al.*, “A Novel Inference of a Restricted Boltzman Machine”, *IEEE International Conference on Pattern Recognition*, Stockholm, Sweden, Aug. 2015, pp. 1526-1531.