DEVELOPMENT OF OPTIMIZED RF CAVITY IN 10 MEV CYCLOTRON

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Abstract

Cyclotron cavity modelled by an artificial neural network, which is trained by our optimized algorithm. The training samples are obtained from simulation results, which are done by MWS CST software for some defined situation and parameters, and also with the conventional BP algorithm. It is shown that the optimized FFN can estimate the cyclotron model parameters with acceptable outputs. Hence, the neural network trained by this algorithm represents the proper estimation and acceptable ability to our structure modelling. The cyclotron cavity parameter modelling illustrate that the neural network trained by the this algorithm could be the acceptable method to design parameters.

INTRODUCTION

An AVF cyclotron is designing for 10MeV energy in the IranCYC10 with straight sectors. It accelerates protons to different energies. The applications of this kind of accelerator are isotope production, nuclear reaction, and nuclear spectroscopy studies for medical purposes [1]. Several small cyclotrons have successfully been developed with compact structure for above applications from 1990s (Sabaiduc et al, 2010). The conceptual design of the cyclotron systems is unchanged from that reviewed in the 1978 conference, but many details have been modified (Peter Miller and Staff, 1981). This cyclotron is included two parallel electrodes, called Dees, in the RF cavity and also couplers and etc., which is part of these structures that can be changed [2, 3].

Our Lab has dedicated to the exploration of the cyclotron physics and key technologies with the compact structure for medical purpose recently. The cyclotron developed by our Lab began by referring to 10 MeV medical cyclotrons. Our cyclotron has room temperature magnets, valley design with four sectors, two Dees in opposite valleys, external ion source and simultaneous beam extraction on opposite lines [4].

The machine learning based system can help to the designer to determine the value of its structure's parameters without time consuming simulations at different and desired situations and values. For example, in our case, a set of parameters required to accelerate a particle to the specific reflected power and frequency. In fact, at the first stage, we tried to find the relation between some of the RF cavity components to these parameters. These components are the coupler disk diameter and its gap, the tuner disk diameter and its gap and the dimension of stems. Figure 1 shows these parameters on a cross section view of the cyclotron cavity [1].

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The feed-forward neural network was the first and arguably the most common type of artificial neural network devised. Feed-forward networks can be constructed from different types of units, e.g. the perceptron. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning. The purpose of a feed-forward neural network is to approximate a function of multiple inputs and outputs. The feed-forward networks belongs to a large category of supervised neural network that can be further broken down based on different training algorithms, e.g., conventional back-propagation (BP) algorithm, generalized regression algorithm, genetic algorithm (GA), etc. Among these algorithms, the BP algorithm is the most extensively studied with huge success in various process modelling and real-time control regimes [5, 6]. Despite the success, as a crude gradient-descent optimization algorithm, it has some inherent disadvantages, including non-convergence, slow convergent rate, over fitting, etc. [1, 7].

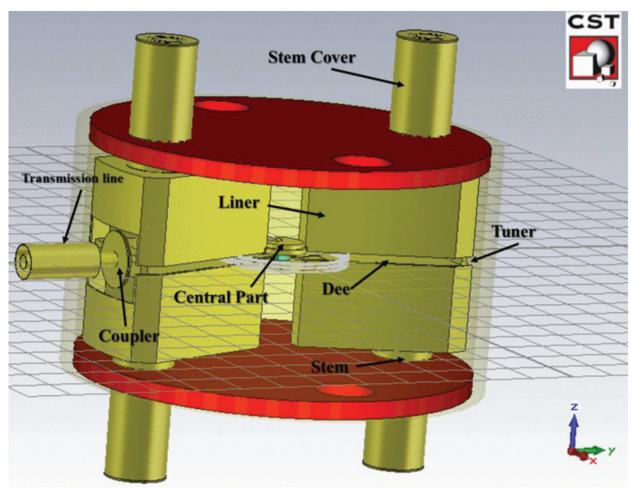

Figure 1: Different parts of the RF cavity of cyclotron.

In this paper, a feed-forward neural network trained and it is improved to simulate cyclotron cavity. We have compared the our algorithm with the BP algorithm in terms of their estimation and generalization ability, which are important in the application of ANN for simulation. As a matter of fact, we have trained an artificial neural network to learn the relation between the cyclotron cavity parameters with its reflected power and resonance frequency. For this purpose, outputs of the CST simulation for some parameters used as network training inputs with known target. So after this step, it can obtain reflected

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power and resonance frequency of any structures for various parameters without any simulations [1].

The RF cavity has been simulated with the general purpose simulation software CST MWS and double checked by HFSS to optimize the resonator characteristics and continues with coupling and tuning optimization.

NEURAL NETWORK ARCHITECTURE

In our case, we will only describe the structure and the behavior of that structure known as the backpropagation network. This is the most prevalent and generalized neural network currently in use.

To build a backpropagation network, first, take a number of neurons and array them to form a layer. A layer has all its inputs connected to either a preceding layer and all its outputs connected to either a succeeding layer or the outputs to the external world, but not both within the same layer [8]. Next, multiple layers are then arrayed one succeeding the other so that there is an input layer, multiple intermediate layers and finally an output layer, as in Fig. 2. Intermediate layers, that is those that have no inputs or outputs to the external world, are called hidden layers. Backpropagation neural networks are usually fully connected. This means that each neuron is connected to every output from the preceding layer or one input from the external world if the neuron is in the first layer and, correspondingly, each neuron has its output connected to every neuron in the succeeding layer.

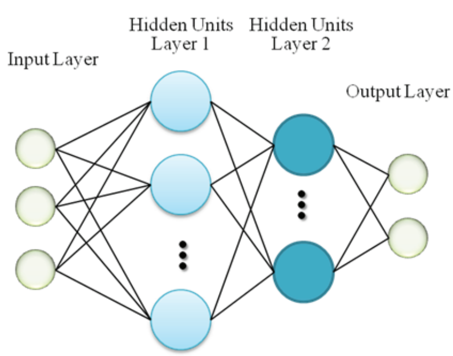

Figure 2: Feed forward neural network with two hidden layers.

The Data Set

Inputs of this network are several parameters of the cavity. Some of them are Stem, Dee and coupling disk parameters. These are the some parts of cyclotron structure. Figure 1 illustrates the cavity structure.

CST MICROWAVE STUDIO SIMULATIONS

CST STUDIO SUITE is a general-purpose simulator based on the Finite Integration Technique (FIT). This numerical method provides a universal spatial discretization scheme applicable to various electromagnetic problems ranging from static field calculations to high frequency applications in time or frequency domain (http://www.cst.com) [9]. Calculations of the created model were performed by means of Eigen mode JD lossfree solver (Jacobi Division Method) in the CST Microwave Studio.

RESULTS AND DISCUSSION

One way to obtain the optimal structure for the neural network, considering the number of neurons in each layer, the connections between neurons and the number of layers is optimizing the results in term of these parameters. So using new optimization methods such as the ANNs can be very efficient. Error of training in our designed network was 2.5e-6. This network includes 4 neurons in input layer, 2 neurons in the output layer, 9 neurons for 1th hidden layer and 15 neurons for 2th hidden layer. Other information of this network was momentum of 0.9, learning rate of 0.5, with 100 training data.

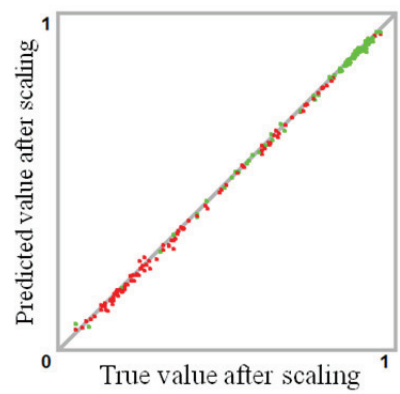

Figure 3: normalized regression between the network outputs and the corresponding targets.

Linear normalized regression between the neural network outputs and the CST simulation output is shown in fig. 3. Red and green dots indicate two predicted outputs.

Some case considered for testing the trained proposed neural network comparing with CST simulation outputs. For example, for each of the parameters, tuner diameter, tuner gap distance, coupler diameter and coupler gap distance values of 50, 1.6, 50, 7.9 respectively, as a neural network inputs, the CST simulation outputs are 72.429,-9.343 for resonance frequency and reflected power and the network estimation outputs are 72.3768, -9.4174. Which they illustrate very small error in estimation.

CONCLUSION

Many points affect to design of the cyclotron cavity, change the scattering parameters and resonant frequency. So finding the proper value for each of them, is too hard. Hence, a procedure which can estimate these values will be very useful.

The results illustrated that the numerical modelling of cyclotron cavity utilizing the artificial neural network structure can create suitable results with proper conformi-

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ty. The simulated outputs for several instances have been done to show concordance with the CST simulation. Therefore, the ANN trained by the our algorithm can be used for parametric consideration of cyclotron cavity.

REFERENCES

[1] M.Mohamadian, H. Afarideh, M. ghergherechi, Optimized Feed-Forward Neural Network Algorithm Trained for Modeling Cyclotron Cavity, *accepted to Chinese Physics C*, (2016).

[2] D. Hungary, Institute of Nuclear Research (ATOMKI). *Hungarian Academy of Sciences, Personal communication*,1996.

[3] M. S.Livingston, J. P.Blewett, *Particle Accelerators*, (Mc Graw- Hill Book Company, 1962).

[4] M. Mohamadian, M. Salehi, H. Afarideh, M. Ghergherechi, J. Chai, Tuner System Optimization in 10MeV Cyclotron Cavity. In *proceedings of the 12th International Computational Accelerator Physics Conference*, (China, 2015).

[5] J. Xia, Rusli, A. S. Kumta, Feedforward Neural Network Trained by BFGS Algorithm for Modeling Plasma Etching of Silicon Carbide. *IEEE TRANSACTIONS ON PLASMA SCIENCE*, 38(2): 142-148 (2010).

[6] M. Abd El- Kawy , M. Shaker Ismail, M. Abdel-Bary, and M.M.Ouda, Artificial Neural Networks for New Operating Modes Determination for Variable Energy Cyclotron, *Arab Journal of Nuclear Science and Applications,* 45(3): (2012).

[7] R. Fletcher, *Practical Methods of Optimization* (Chichester, U.K.: Wiley,1987).

[8] L. Fausett, Fundamentals of Neural Networks. Prentice Hall. New York. (1994).

[9] CST Studio Suite 2014 (CST Microwave Studio).

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