DESIGN OF NUCLEAR POWER CONTROL SYSTEM BASED ON ARTIFICIAL NEURAL NETWORK LEVENBERG MARQUARDT AT THE NUCLEAR TECHNOLOGY CENTER FOR MATERIALS AND RADIOMETRY -- NATIONAL NUCLEAR ENERGY AGENCY (PTNBR BATAN) BANDUNG

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ABSTRACT

Fission reaction occurs in the inside of reactor tank between the nuclear fuel and neutrons. Fission reaction causes rise and fall of nuclear power reactors. In order to control the nuclear power reactor used five control rods which is moved up and down inside the reactor tank. There is a complex process and non-linear modeling in the reactor tank, conducted modeling reactor tank with Artificial Neural Networks with the structure of the Multi Layer Perceptron (MLP). The structure is a structure model derived from Nonlinear Auto Regressive with external input (NARX). Weights controlling of neural networks was carried out using Levenberg-Marquardt algorithm, which could give good results with RMSE and VAF good enough, ie 0.0209 and 98.8682. After getting the tank reactor model, then the reactor power control system designed using the Direct Inverse Control based on Artificial Neural Networks. The simulation results show a direct inverse control system based on neural networks have a good response. Direct inverse control follow the set point with maximum overshoot 0% for all set point.

Keywords: nuclear power, reactor tank, artificial neural networks.

I. INTRODUCTION

The control system is consist of one or more equipments are used for controlling other systems that related with a process. In an industry, all process variables such as power, temperature and water flow rate should be monitored at all times. If the current process variables are not as expected (set point), then the control system can control the process so that the system can be running again as expected. The control system can be used in factories, buildings and in Nuclear Power Plant (PLTN).

To control the system that have very complex process and a plant which is very sensitive are like Nuclear Power Plant (PLTN), nuclear reactor control system by using either manually control or automatically control with a conventional control (PID control) has a disadvantage because their performance on manual control is very dependent on the physical and mental condition of psychological operators, while in PID control error, overshoot and settling time is quite long. In addition, the nuclear reactor has a variable non-linear dynamics and changes as well as mathematical models of nuclear reactors and fission reactions are very complex and complicated for it's not easy to use optimal control system as the reactor control system because this system requires a mathematical model that connects between the input (input), process and output (output) in order to control a plant. To overcome this weakness, the control system of neural networks (NN), Levenberg Marquardt could be an alternative to nuclear reactor control systems used in nuclear power plants (PLTN).

II. LITERATURE

2.1 Nuclear Reactor Power Control

To increase the reactivity (power reactor) is by pulling the control rods from the reactor core. If the control rod is pulled out from the terrace, reactivity or fission reaction increases and produces more heat energy (the reactor power rises). This heat energy to boil more water, and thus the steam produced is also increasing. The increase in water vapor content will decrease the ability of water in a moderate neutron particles. The number of low-speed neutrons (thermal neutrons), which would cause a fission reaction to be reduced, so that the result of fission reactions (reactivity) was also reduced. So raise the reactor power by pulling the control rod will always be compensated by the pressure steam production power. This compensation process will end in a stable condition at a certain equilibrium power. Conversely if the control rod inserted into the core, is reduced by the presence of fission neutron absorber (control rod) in the core. Production of steam produced is also declining because of the production of thermal energy from fission reactions decreases. Consequently the ability of water in moderate neutrons increases, and the fission reaction will begin to rise. Power reduction process by the control rod which was then offset by a decrease in power due to improve moderation capabilities will continue to achieve a stable condition at a certain equilibrium power. The phenomenon of compensation by the steam-water become one important tool in self-control (self control) is one of the reactors.

2.2 Neural Network

Making the structure of neural networks was inspired by the biological tissue structures, particularly the human brain tissue. Artificial neural network consists of several neurons, and there is a connection between these neurons. Neurons will transform the information received through the connection leading to the release of other neurons [9]. Neural network system

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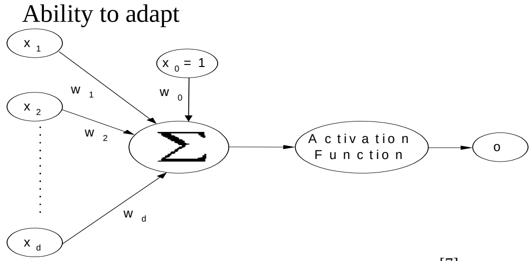
is characterized by the existence of the learning process (learning) that serves to adapt the network parameters. The advantages of artificial neural networks are:

- Able to make the learning process
- Ability to adapt



Picture 2.1 neural network structure [7]

Algorithms learning and Neural network structures used in this study is Levenberg Marquardt algorithm and Multilayer Perceptron (MLP). Levenberg Marquardt algorithm has faster convergence characteristics advantages (rapid convergence), in mathematically pair of input and output data relation can be written as follows:

$$Z^N = \{[u(t), y(t)], T = 1, \ldots, N\} \quad \ldots(2.1)$$

The purpose of the training is to get a pair of mapping data to a pair of candidate models.

$$Z^N \rightarrow \hat{\theta} \quad \ldots(2.2)$$

so we get a model that provides a prediction of output *ŷ(t)* the same or close to the output y (t). The most common method used to measure the similarity between the model output with the model is actually a type of mean square error criterion.

$$V_N(\theta, Z^N) = \frac{1}{2N}\sum_{t=1}^{N}[y(t) - \hat{y}(t|\theta)]^2 = \frac{1}{2N}\sum_{t=1}^{N}\varepsilon^2(t,\theta) \quad \ldots(2.3)$$

Multilayer Perceptron (MLP) network is most often considered members of a family of artificial neural networks. The main reason is simply the ability to model complex functional relationships. Mathematical formula that expresses what is happening on the network-MLP was taken from:

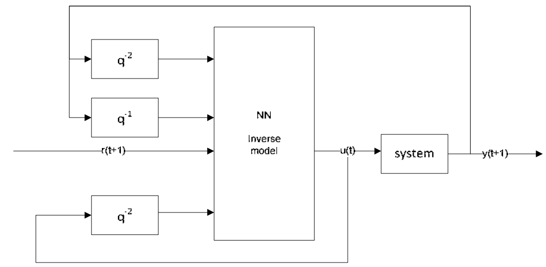
$$\hat{y}_i(t) = g_i[\varphi, \theta] = F_i\left(\sum_{j=1}^{n_h} W_{i,j} f_i\left(\sum_{l=1}^{n_\varphi} w_{j,l}\varphi_l + w_{j,0}\right) + W_{i,0}\right)$$

..(2.4)

θ shows the vector parameter in which there all the parameters of ANN, which can be set (weights and biases).

2.3 Control system by Neural Network

Application of neural networks is for a control system. Characteristics of neural networks as non-linear system is very suitable for a non-linear control systems. Artificial neural network used in this final project is the Direct Inverse Control. This control is the most basic concepts of control based on neural networks that use the inverse as a control process. The most basic concept is called direct inverse control, as shown in Picture 2.2.



Picture 2.2 Direct Inverse Control[7]

The principle of this process can be described as follows:

$$y(t+1) = g[y(t) \ldots, y(t-n+1), u(t), \ldots, u(t-m)] \quad \ldots(2.5)$$

Network used to train the inverse process is:

$$\hat{u}(k) = \hat{g}^{-1}[y(t+1), y(t), \ldots, y(t-n+1, u(t), \ldots u(t-m)] \quad \ldots(2.6)$$

Then the inverse model was applied as a control for a process by entering the desired output. Before the actual control system worked the inverse model must be trained. Learning methods for neural network based control can be divided into two methods, namely:

1. Generalized Training

In this method, artificial neural networks are trained offline to minimize the mean square error (MSE) in the control signals which are applied to the process through experimental control signals generated from the network.

2. Specialized Training

This method serves to minimize the mean square error (MSE) between the reference signal and the output of the process. This method works well online by using a recursive algorithm training.

III. DESIGN AND METHODOLOGY

In this chapter will discuss the stages of designing a nuclear reactor control systems. System to be designed is divided into 2 (two) main parts, plant and control systems. Important element in nuclear reactor control system is the control rod. Control rod position will be controlled to obtain the amount of output reactivity associated directly with the amount of power produced by the reactors. In addition, control rod also controls the primary coolant system temperature in the reactor core.

In designing a control system using neural networks, basically consists of three main stages in accordance with the concept of artificial neural network (the learning phase from the phase of usage) is modelling the plant, the controller offline training (learning phase) and the online training controller . Each of these stages should be carried out simulations to see the response of the plant structure of neural networks in the form of certain weights and biases of the plant really is. Furthermore, in the offline controller training carried out in order to obtain initial weights and biases of the controller to be used in online training. And to see the capability of overcoming the set point and disturbance changes must be made online by combining training neural networks and neural network plant model obtained from the previous stage.

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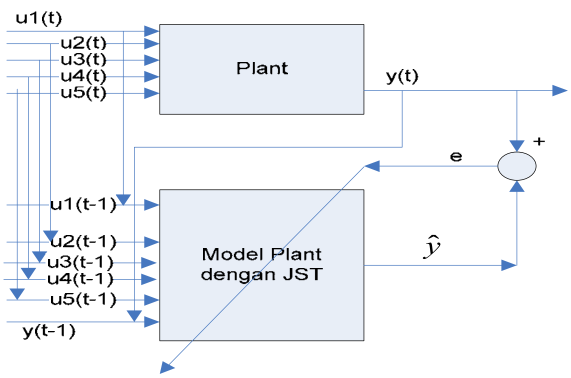
3.1. Modeling Plant by Neural Network

Based on the input and output data that has been determined by using neural network learning methods will be sought which can present the model plant dynamics of the reactor power control process. In the identification process by using neural network, the input data used is the fifth position of control rods. While the output data was used in the reactor core reactor power. Here is a block diagram of process modeling using neural networks.



Picture 3.1 Block diagram of the plant modeling by Neural Network [7]

Modeling plant by neural network using five inputs, 1 reference input from the output of the plant to be learning in order to get the output from the plant using neural network modeling is the modeling process in which a desired output. Input at this plant modeling using input variables that enter into the reactor plant, which is variable u1 (t) is the input control rod position 1, variable u2 (t) is the input control rod position two, variable u3 (t) is the input control rod position 3, the variable u4 (t) is the input control rod position and variables four u5 (t) is the input control rod position 5. Data input and output processing plant at the time of the past (u (t-1), u (t-2), ..., u (tn)) to input data to generate predictive ANN model output. The data in the past used to train the network to achieve the desired weight. During the learning of these data is given to the network then the network will process and issue output.

Then the output data was compared with the plant output data (y (t)) is actually to know how much error (e) incurred. In this learning process is the smallest error sought continually to obtain the small error, this is commonly known by the term iterative process to obtain the appropriate weights to obtain the output value of neural network model plant in accordance with predetermined criteria parameters.

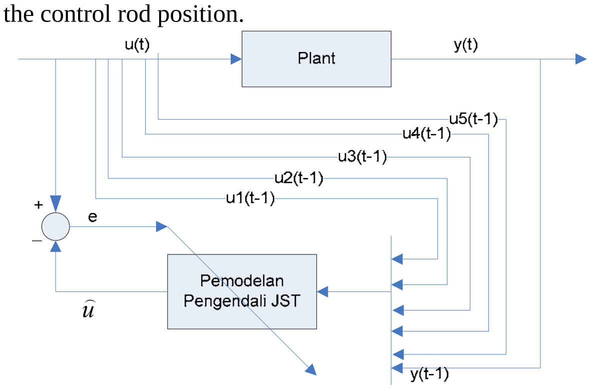
From the 326 real plant history data, selected data will be used for learning or training process by neural network modeling and validation for the plant. By using the architecture of the Multi Layer Perceptron (MLP) where in this architecture there are three layers namely input layer, hidden layer and output layer. In each layer there is an activation function embedded on the network architecture. Activation function in hidden layer uses hyperbolic tangent, while the output layer uses linear activation functions. To get a good ANN model plant, so it can predict well the process output, neural network structure was tested by replacing-changing network structure. Among them is the number of hidden nodes and total length history.

Learning algorithm used in this study is the Levenberg Marquardt algorithm. Levenberg Marquardt algorithm has faster convergence characteristics advantages (rapid convergence), however the algorithm is Levenberg Marquardt algorithm requires more complicated than the decline in back propagation algorithm.

The purpose of the training process is to get the weights that produce the best output. The criteria used to assess the output is the Root Mean Square Error (RMSE) and the Variance Accounted For (VAF). If the model output has complied with RMSE and VAF value is best derived from the weight training process that is w1f (weights from input layer to hidden layer) and w2f (weight from hidden layer to output layer), hidden node as well as the history length is stored as a forward for use on the stage of validation and simulation of Direct Inverse Control.

3.2. Modeling Control by Neural Network

Process modeling using neural network controller has the same concept with modeling plant using neural network, still using the relationship of input and output, only input and output data usage is now reversed. For controlling the model input data used is the reactor power, while the output data used is the control rod position.



Picture 3.2 Block diagram of the control modeling by Neural Network [7]

Just as the modeling of plants, first normalizing the data by performing data scaling or normalizing the data to be in the range 0-1. Furthermore, the data is validated by ANN trained to generate outputs in the form of modeling. Then the data controller model output was compared with the plant input (u (t)) is actually to know how much error (e). From these error values to be used for member information to update the ANN weight values continually until the results is that small errors in modeling the controller.

From the 326 real plant history data, selected data will be used for learning or training

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process and validation of modeling with neural network controller. If the model output has complied with RMSE and VAF value is best derived from the weight training process that is w1i (weights from input layer to hidden layer) and w2i (weight from hidden layer to output layer), hidden nodes and the length is stored as an inverse history for use on the stage of validation and simulation of Direct Inverse Control.

3.3. Performance Criteria of Neural Network Modeling

The criteria used to assess the neural network model using Root Mean Square Error (RMSE) and Variance Accounted For (VAF).

- RMSE is the root of the average total squared error between model output, and output processes. The smaller RMSE value (approaching zero), then the greater the success rate of training, on the contrary the greater the value the smaller the RMSE the success rate of training. RMSE value equation can be written as follows:

$$RSME = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \qquad ...(3.1)$$

- VAF
  also stated in the VAF (Variance Accounted For) in percent. With the stipulation that the greater the value of VAF (approaching 100 value) then the greater the success rate of training. VAF equation can be written as follows:

$$VAF = \left\{1 - \frac{var[y(t) - \hat{y}(t)]}{var[y(t)]}\right\} x100\% \qquad ...(3.2)$$

3.4. Simulation of Direct Inverse Control

Direct inverse control is one of the neural network based control system with controls that are connected in series between the model neural network controller and neural network plant model.

From the results of modeling plant training to obtain the weight, length and number of history hidden node that is integrated in the forward as a model plant to be used in the simulation of DIC. Similarly the results of modeling training controllers to obtain the weight, length and number of history hidden node that is integrated in the inverse model controller that will be used in the simulation of DIC.

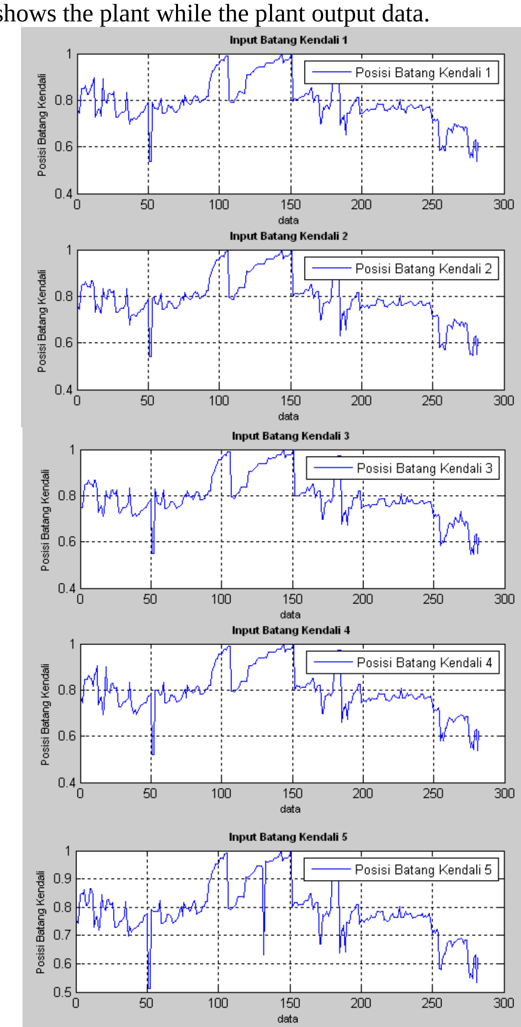
To determine the success rate of direct simulation, inverse control based neural network was done by set point tracking test with the parameter value of maximum overshoot (Mp) and the settling time (ts) from the controller that produced by the response.

IV. ANALYSIS AND SIMULATION

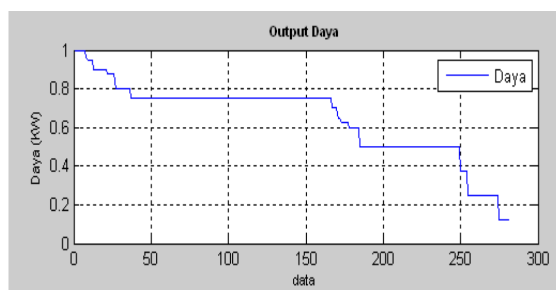
4.1 Input Output Data Plant of Nuclear Reactor

Plant which is modeled is Nuclear Reactor at the Nuclear Technology Center for Materials and Radiometry (PTNBR) BATAN Bandung. Data used in modeling are the control rod position as a data input and output data as the reactor power.

Input-output data taken from real plant for three years, so the total data obtained were 357 data. The amount of data that was used is 326 data, because there are data that was recorded when the plant was shut down. Graph 4.1 shows the input data graph 4.2 shows the plant while the plant output data.



Graph 4.1 Input Data Plant



Graph 4.2 Output Data Plant

4.2 Analysis of Modeling Plant by Neural Network

Modeling of plant by neural network are through two stages, training and validation. For modeling of plant, input data and target data were obtained from real plant, of all existing data will be divided into two for use in training and validation. After a few experiment, on this final project, the most optimal is to use 282 data for training and 44 data for validation. Modeling conducted by Artificial Neural Networks, Multi Layer Perceptron (MLP). In this final project, neural network architecture consists of three

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layers namely input layer, hidden layer and output layer. The variables used in neural network is as follows: input (u), output (y), weights from input layer to hidden layer (w1f), weights from hidden layer to output (w2f). Plant consists of five inputs and one output, so the model output equation can be given by:

$\hat{y} = f(y, u1, u2)$ … (4.1)

with :

$\hat{y} = [y(k), y(k-1), \ldots, y(k-ny)]$

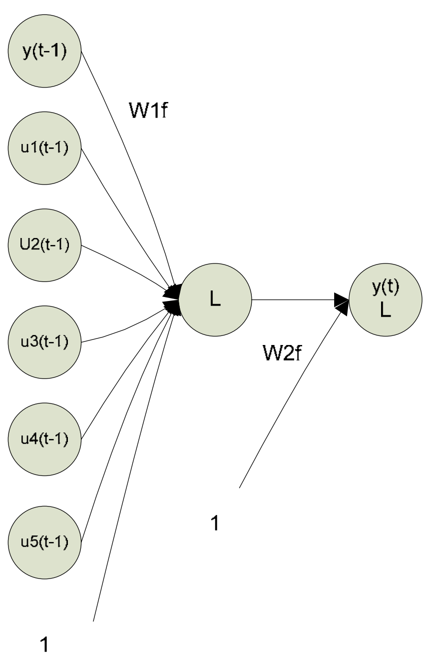
$u1 = [u_1(k), u_1(k-1), \ldots, u_1(k-nu_1)]$

$u2 = [u_2(k), u_2(k-1), \ldots, u_2(k-nu_2)]$

f= activation function

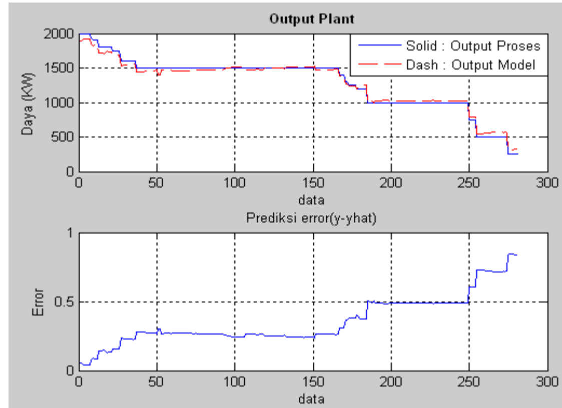
where ny and nu are history length for output and input process. Activation function which is used in hidden layer and output layer are linear.

The first procedure in modeling by neural network is experiment. Experiment here is to get the best model by changing neural network parameters such as hidden node, history length and activation function. Experiment is conducted by changing the value of history length from 1-5 and by changing the hidden node from 1-15 to get the smallest value of RSME and the highest value of VAF.



Picture 4.1 NN Structure for modeling plant

After doing the experiment was obtained the best results with one history length and one hidden node. Activation function were used in hidden layer and in the output layer are linear activation function, that structure resulting RMSE = 0.0209 and VAF = 98.8682. Graph 4.3 shows the inputs was used to process the 326 training data, graph 4.4 shows the power output as a pair of every data input position control rod, while the graph 4.5 shows the comparison between real plant output with the output of the neural network.



Graph 4.5 Output Training modeling plant and error

The graph above is a graph that shows comparison between real plant output (blue) with an output of neural network model (red), and errors that occur in each pair of data. After conducted the training process will be generated a weight w2f and w1f, the value of this weight is stored for use in the validation process. In the validation data set was used 44 data that is not used in the training process. In the validation process produced RMSE= 0.1261 and VAF = 83.2816.

4.3 Analysis of Modeling Control by Neural Network

Modeling control with neural network has the same steps with neural network modeling plant, the different is the structure of neural network that used to modeling control is the inverse of the neural network structure that used in modeling plant, or it can be said controller is the inverse modeling of modeling plant. Then the modeling data for modeling controller set used is the power demand from operators as input data and the position control rod as output data. The first stage is to find the best structure of neural network, then conducted experiments by changing the value of history length and a number of hidden nodes to obtain the smallest RMSE value and the highest value of VAF.

The best architecture of neural network for modeling control are with one history length and 30 hidden node. Activation function was used in hidden layer and output layer are linear.

In the training process produces RMSE = 0.0178 and VAF = 96.5654 for control rod position 1, output control rod position 2 produces RMSE = 0.0161 and VAF = 97.2107, output control rod position 3 produces RMSE = 0.0137 and VAF = 97.9039, output control rod position 4 produces RMSE = 0.0189 and VAF = 96.1168, output control rod position 5 produces RMSE = 0.0262 and VAF = 92.5715. Graph 4.11 is the comparison between real plant output with the output of neural networks to control rod position 1, 4.12 graph shows the comparison between real plant output with the output of ANN control rod position 2, graph 4.13 is the comparison between real plant output with the output of neural networks to control rod position 3, graph 4.14 shows the comparison between real plant output with the output of neural network control rod position 4 and graph 4.15 is a comparison chart between the output of real plant with an output of

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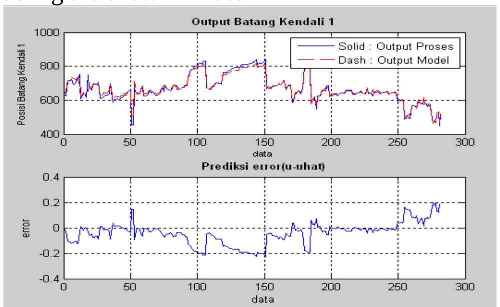
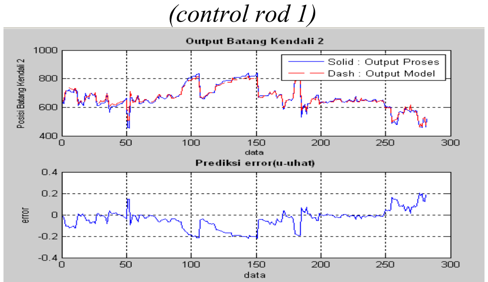
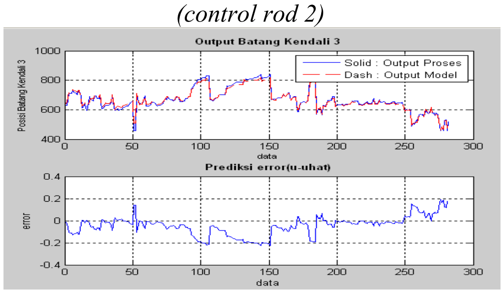
neural networks to control rod position 5. Plant output is shown in blue while the output of neural network modeling are shown in red.



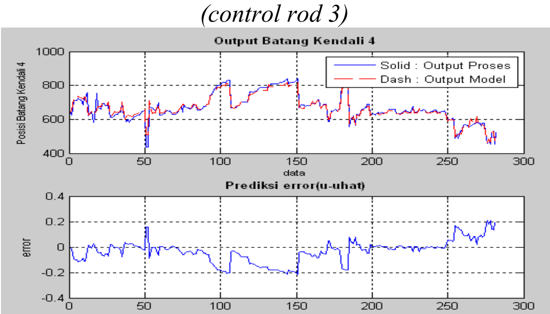
Graph 4.6 Output Neural Network Training and Error (control rod 1)



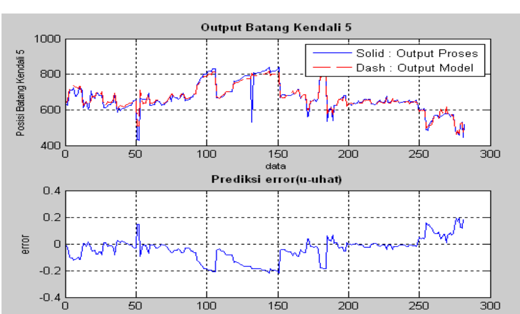
Graph 4.7 Output Neural Network Training and Error (control rod 2)



Graph 4.8 Output Neural Network Training and Error (control rod 3)



Graph 4.9 Output Neural Network Training and Error (control rod 4)



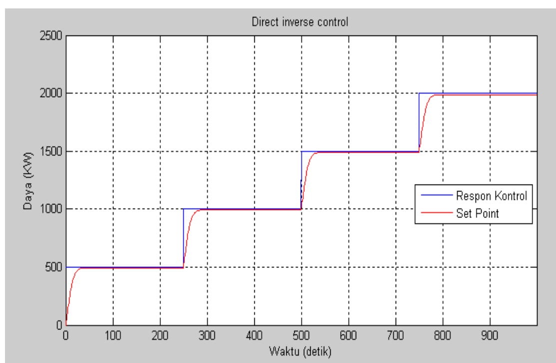
Graph 4.10 Output Neural Network Training and Error (control rod 5)

After conducted the training process will be generated weights (w2i and w1i), the value of this weight is stored for use in the validation process. In the validation process used 44 data which is not used in the training process.

In the validation process produced RMSE = 0.0185 and VAF = 87.1010 for the output of control rod position 1, for output control rod position 2 produces RMSE = 0.0137 and VAF = 92.4092, for output control rod position 3 produces RMSE = 0.0129 and VAF = 91.8641, for output control rod position 4 produces RMSE = 0.0278 and VAF = 70.5352, for output control rod position 5 produced RMSE = 0.0098 and VAF = 94.9508. Graph 4.6 is the comparison between real plant output with the output of neural networks for control rod position 1, graph 4.7 shows the comparison between real plant output with the output of neural network control rod position 2, graph 4.8 is the comparison between real plant output with the output of neural networks to control rod position 3, graph 4.9 shows the comparison between real plant output with the output of neural network control rod position 4 and graph 4.10 is a comparison chart between the output of real plant with an output of neural networks to control rod position 5. Plant output is shown in blue while the output of neural network modeling are shown in red.

4.4 Direct Inverse Control

After did the modeling plant and modeling control with neural network, we get the weight of the modeling of plant (W2f and W1f) stored in a file forward and the weight of the modeling control (W1i and W2i) stored in the file inverse. Weights are used to simulate the direct inverse control. Simulation is done by changing the set point value as much as four times, namely at 500, 1000, 1500, 2000. Graph 4.11 shows the response system of direct inverse control.



Graph 4.11 Simulation Direct inverse control based Neural Network

From the graph of the control response system above the response is obtained on 1000 data, this ratio control is good enough in the set point tracking. Direct inverse control follow the set point with maximum overshoot 0% for all set point.

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V. Conclusion and Suggestion

5.1 Conclusion

From the simulation results and analysis of data on this final study, several conclusions can be drawn, among others:

1. Modeling plant with the best neural network obtained at 1 history length and number of hidden nodes 9 produced RMSE = 0.0209 and VAF = 98.8682.
2. Direct Inverse Control Simulation of system response obtained good results, it can be known from the tracking set point. Control of power reactor can follow the set point with maximum overshoot 0% for all set point.

5.2 Suggestion

Some suggestions that need to be addressed in this report in order to develop this research are as follows :

1. To develop this research, there needs to be done recording method of better data, for example by recording the data in greater numbers.
2. To develop this research should be conducted the study using a model that other structures such as NNOE, other learning algorithms, like Gauss Newton.
3. Need to be applied online at the real plant in future studies.

REFERENCE

[1] Gayani, Didi. 2010. **Instrumentasi dan Kendali Reaktor, Kursus Penyegaran bagi Operator dan Supervisor**. Bandung.

[2] Eli, Yani. **Pengantar Jaringan Syaraf Tiruan.** Materi Kuliah.com

[3] Fredi,A.Nugroho.2008.**Perancangan Sistem Pengendalian Level Air pada Deaerator Tank di PT.IPMOMI dengan Jaringan Syaraf Tiruan.** Surabaya: Tugas Akhir Jurusan Teknik Fisika. ITS.

[4] Katsuhiko,Ogata.1994.**Solving Control Engineering Problems with MATLAB.**New Jersey:Prentice-Hall, Inc.

[5] Pradanggapasti.2007.**Perancangan Sistem Pengendalian Temperatur ILC dan SLC untuk Umpan Kiln dan Raw Mill Pada Preheater dengan Jaringan Syaraf Tiruan di Semen Gresik.**Surabaya: Tugas Akhir Jurusan Teknik Fisika. ITS.

[6] Fauset, L. 1994. **Fundamental of Neural Network. Architecture,Alogorithm, and Aplication**. New Jersey: Prentice Hall.

[7] Magnus Nørgaard, Ravn, O. Poulsen, N.K. dan Hansen, L.K. 2000. **Neural Network for Modelling and Control of Dynamic Systems.** London: Verlag Springer.

[8] Siang, J ong Jek.2009. **Jaringan Syaraf Tiruan & Pemro-gramannya menggunakan Matlab**. Yogyakarta. Penerbit Andy.

[9] Effendy, Nazrul, Achmad, Balza dan Hawibowo, Singgih. **Optimasi Jaringan Syaraf Tiruan untuk Kendali Daya Reaktor Riset KARTINI dengan Model Referensi Linier.** Yogyakarta.

[10] Hasan. Gayani, Didi. Sudjatmi. Deden. **Analisis Kestabilan Reaktor dengan menggunakan Persamaan Liapunov.** Bandung.

[11] Setiadi, Agus Chris 2008. **Perancangan Sistem Kontrol Tegar h∞ untuk Optimisasi Pembakaran pada Boiler PT. Petrokimia Gresik**. Bandung : Tugas Akhir Program Studi Teknik Fisika - Institut Teknologi Bandung.

[12] Maurice Stewart, Ken Arnold, 1991. **Surface Production Operations-Volume1-Design of Oil-Handling Systems and facilities**. London: Gulf Publishing Company.

[13] Dias, M. Fernando., Mota, M. Alexandre., 2000."Direct Inverse Control Of a Kiln". **Proceeding Departamento de Engenharia Electrotécnica,Campus do IPS, stefanilha, 2914-508 Setúbal, Portugal.** CONTROLO 2000.

[14] Gunterus, Frans.1994.**Falsafah Dasar:Sistem Pengendalian Proses**. Jakarta: Elex Media Komputindo.

[15] Sudiono, Kodar. **Perancangan Sistem Pengendalian Dan Optimasi Rasio Aliran Udara Dan Bahan Bakar Pada Boiler Di PT. Petrokimia Gresik Berbasis Jaringan Syaraf Tiruan Dan Algoritma Genetik.** Surabaya: Tugas Akhir Jurusan Teknik Fisika. ITS.

[16] Agung, Alexander. **Dinamika Reaktor Nuklir.** Yogyakarta: Diktat Kuliah Jurusan Teknik Fisika. UGM.

[17] Cruz, José Humberto Pérez. Read,Jorge Samuel Benítez, Gorbatch,Alexander Poznyak. 2007. **On The Observa-bility of The Point Kinetic Equations of a Nuclear Reactor.** Mexico

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