Modelling of 330MW Circulating Fluidized Bed Boiler System Based on Deep Belief Network

Zhonghao Xiong*, Yiwei Lin, Xin Li, Jian Yang

1 Datang Hydropower Science & Technology Research Institute Co., Ltd, Nanning, Guangxi, 530007, China
2 Corresponding author’s e-mail: 413328265@qq.com

Abstract. Circulating Fluidized Bed Boiler (CFBB) is an important part of thermal power plants. The plant's control system is a complex multivariable system with severe nonlinearities, uncertainty and strong coupling. It is not accurate to use traditional analysis methods to build mathematical models of the system. This paper introduces the modelling method of 330MW circulating fluidized bed boiler coordinated control system based on deep belief network (DBN), using the in-situ data of Inner Mongolia Jinghai Power Plant. Compared with the BP neural network modelling method, the effectiveness of the DBN method in the modelling of 330MW circulating fluidized coordinated control system is proved.

1. Introduction

In 1979, Ahlstrom of Finland developed the world's first commercial circulating fluidized bed boiler [1]. China's circulating fluidized bed technology began in the early 1980s. After 35 years of research and development, China has mastered the advanced design theory and manufacturing technology of circulating fluidization, forming a series of capacity products from small-capacity steam boilers to large-scale supercritical power generation boilers [2]. Circulating fluidized bed boiler is the second generation of fluidized bed boiler developed from bubble bed boiler. As a clean coal-fired technology, it has the following advantages: wide fuel adaptability, high combustion efficiency, efficient desulfurization, low emission of nitrogen and oxygen compounds, etc. [3].

One of the research difficulties of CFB boilers is CFB modelling and related control. Only a precise model can achieve a good control effect. The difficulty in modelling circulating fluidized beds is that they are severely constrained by special combustion methods. These complex combustion relationships are not yet fully understood [4]. The modelling of CFB boilers can be divided into two categories, mechanism modelling and experimental modelling. In order to analyse the characteristics of the fluidized bed boiler and reveal the basic laws of the combustion process in the furnace, according to the basic principles and assumptions of the theory of fluid mechanics and heat transfer, the mechanism model established for different phase types and working conditions in the furnace is established. In 1993, Luo Zhongyi established a mathematical model for the combustion of coal-fired circulating fluidized bed [5]. The accuracy of some parameters in quantitative calculation still needs further development. Subsequently, Ni Weidou et al. used Tsinghua 220t/h circulating fluidized bed. The boiler is the object, and a general mathematical model of a circulating fluidized bed is established [6]. The model considers three points: the wide screening characteristics of coal and bed materials, the use of "chamber models", and the generation and reduction of volatiles. All this makes this model a sophisticated and powerful functional model of circulating fluidized bed boilers; Subsequently, the modelling of CFB is developing towards large scale. In 2014, Gao Mingming established the
mechanism dynamic model of bed temperature, main steam compressor and power according to the coupling relationship between various variables of the coordinated control system. Furthermore, the three models are combined into the coordinated control system model of CFB boiler.[7]. Due to the complex nature of circulating fluidized bed boilers and running combustion, the modelling process encounters many difficulties. At present, there are two problems in mechanism modelling: 1) The model is complex. The established model often contains a large number of nonlinear higher-order equations, and it is difficult to find an effective method for simulation. 2) The model is not accurate. There are many empirical formulas and approximation formulas in mechanism modelling. Even if the simulation results are very good, there are still big differences with the actual boiler operation. Mechanism modelling is difficult to meet the design of the control system, so field experiment modelling is particularly important. The experimental modelling method is to control the input and output characteristics of the control system for the purpose of designing the control system of the fluidized bed boiler. The model is generally determined by field experiments and system identification methods. Field experiments usually use methods such as step response and random disturbance. There are many methods for system identification. The common methods are least squares and some intelligent identification methods, such as fuzzy identification and neural network identification. In 2000, Niu Peifeng proposed a human-like intelligent control system. The system has passed the expert appraisal. After the actual operation of the system, the system has achieved good control effect on the main steam pressure, bed material temperature and furnace negative pressure. [8]. Due to the complicated experimental conditions on site, and the relevant data of major manufacturing and research units in China are not willing to disclose, there are not many scholars engaged in this research. With the advancement of industrial technology, a large number of enterprise factories store a large amount of production process data every day, and data-driven modelling control methods are generated and developed in this context. Because it only needs the system I / O data to complete the controller design, to achieve various desired functions of the system based on data forecasting, evaluation, scheduling, monitoring, diagnosis, decision-making and optimization, by the process control engineer favorite[9]. Research on data-driven modelling control becomes extraordinarily meaningful when object-free or mechanistic models are inaccurate. The modelling of circulating fluidized bed has the problem of inaccurate mechanism model. The neural network data-driven modelling method has emerged in the past decade, and has become the focus of many scholars in the research of circulating fluidized bed boiler modelling. The neural network algorithm has the ability to learn the mapping relationship of complex nonlinear functions, and it provides a nonlinear system modelling and control framework. Due to the rise of industrial computer control, many power plants are equipped with DCS or SIS equipment, which has a large amount of historical data, which is very beneficial to the research of modelling, identification and control of circulating fluidized bed by neural network algorithm. In 1997, Ye Haiwen initially studied the modelling of coal-fired circulating fluidized-bed boilers using multi-layered forward nerves. It was found that the trained neural network can not only accurately reproduce the existing calculation results of the mechanism mathematical model, but also accurately and The mechanism model predicts the performance of the boiler as well [10]. Subsequently, the theory and method of circulating fluidized bed modelling using wavelet neural network, BP neural network, fuzzy neural network and α-order inverse neural network were introduced [11-17].

The neural network and the improved neural network method have achieved good results in CFB boiler modelling, but the following problems still exist: 1) the overall CFB mathematical model is not effective; 2) in the case of large changes in working conditions The accuracy is difficult to guarantee; 3) the initial weight is sensitive, and it is easy to fall into the local minimum; 4) the over-fitting phenomenon is easy to appear; 5) when the number of neural network layers is increased to 4 or even more layers, the gradient disappears, causing the network Training failed. These shortcomings of the neural network make it greatly hindered in the application process in order to effectively solve these shortcomings. In 2006, Hinton published a paper Science [18], which first proposed an unsupervised greedy layer-by-layer network parameter algorithm and named the network as Deep Belief Network.
(DBN). Through the stacking of the restricted Boltzmann machine (RBM), the layer-by-layer greedy pre-training weight matrix mitigates the problem of multi-layer neural network gradient disappearance, overcomes the problems of the BP algorithm, and successfully trains the hidden layer for the first time. A 3-layer deep neural network with good results on many public test sets.

The deep belief network can extract deeper data features, effectively prevent the gradient from disappearing and over-fitting, and use the contrast divergence algorithm to ensure the fast convergence of the network and meet the industrial requirements for computing speed [19]. However, through extensive literature searches, the authors note that circulating fluidized bed modelling techniques based on deep belief networks have not been widely reported. In this paper, the modelling method of circulating fluidized bed based on deep belief network is explained in detail. The validity of the model is verified by the actual data of the 330WM circulating fluidized bed boiler of Jinghai Power Plant in Inner Mongolia, and compared with the BP neural network modelling results. The results prove that the deep belief network modelling method has more accurate prediction results than BP neural network.

2. Modelling Analysis of Circulating Fluidized Bed Boiler

For large-scale power generation systems, boilers, steam turbines, and generators combine to respond to changes in load demand generated by the power system network and maintain their stability. In order to minimize the effects of plant-wide interactions and disturbances to ensure a higher rate of load change, a coordinated control strategy is required.

The typical load structure control does not consider the overall coordination of the circulating fluidized bed boiler turbine control system, and cannot achieve satisfactory control results. Part of the combustion control system is the focus and difficulty of circulating fluidized bed modelling. Bed temperature is a unique process parameter for CFB boilers and a key factor in efficient boiler operation. CFB boiler coordinated control system modelling has the following two difficulties:

1. Strong coupling, in a drum boiler, the entire system is usually broken down into three simplified subsystems, the fuel system, water supply system and steam temperature system. The fuel system and the feedwater system directly determine the steam temperature, resulting in a strong coupling effect between the boiler parameters.

2. Strong inheritance nonlinear characteristics: The load cycle operation of the generator set causes the operating point to change throughout the working range, and the steam pressure is mainly between 10 and 18 MPa. The nonlinearity of the parameter variables becomes more severe.

It is necessary to coordinate the relationship between bed temperature - main steam pressure - output power to establish an effective CFB coordination system control model. Figure 1 shows the coupling relationship between input and output.

Through the coupling relationship of the CFB boiler turbine coordination system, we can simplify the model and establish a three-input three-output CFB coordinated control system model, as shown in Figure 2. \( y_1, y_2, y_3 \) represent the main steam pressure, bed temperature and output power, respectively. \( u_1, u_2, u_3 \) are the coal supply quantity, the primary air volume and the valve opening degree, respectively.
The selected inputs and outputs can truly reflect the dynamic characteristics of the system. In this paper, 10,000 sets of field input and output data are used as the training data of the deep belief network, and another 5000 sets of field input and output data are used as the validation data, and the sampling interval is 5s. The data is shown in Figure 3 and Figure 4.

3. Modelling Analysis Based on Deep Belief Network

Deep Belief Network (DBN) pre-trains data in a greedy and unsupervised manner by superimposing multiple restricted Boltzmann machines (RBMs) layer by layer, obtaining well-distributed data expressions, and then using supervised methods. (BP algorithm, gradient steepest descent method, etc.) adjust the parameters of the entire network. The core of the DBN can be divided into two parts: RBM and CD algorithms. RBM is both a random neural network and a recurrent neural network. The feedback connection is used to consider the transmission delay on the output and input. It represents a dynamic process and can express the nonlinear dynamics of the system. DBN better simulates the deep structure of human brain perception information and processing information, and realizes effective and rapid learning of large amounts of data. It has been successfully applied to pattern classification, prediction, combination optimization and planning. In this paper, the deep belief network structure of double hidden layer structure is used. The double hidden layer network has better ability to propose features than the single hidden layer network, which meets the demand for the accuracy of time series prediction problem, and also meets the demand for rapid calculation in the industrial process.

3.1 Deep belief network overview

The Deep Belief Network (DBN) is superimposed by several restricted Boltzmann machines (RBMs). The DBN is structurally a forward recursive network. In the forward channel, each RBM is trained one by one in an unsupervised manner. The output of the first restricted Boltzmann machine is used as the second restricted Boltzmann. The input of the machine obtains the pre-training optimal parameters of the RBM, and the parameters obtained by the first layer RBM are taken as the initial values of the DBN. In the reverse channel, fine-tuning of the weights is performed by a supervised algorithm. After a lot of practice, it is found that the DBN network with double hidden layer or three layers of restricted Boltzmann machine can achieve very good results. If the number of layers is increased, the pre-training time will be greatly increased and the network will be converged. Slower speeds are not conducive to predictive analysis. A typical DBN network structure is shown in Figure 5:
Figure 5. DBN network structure

After the unsupervised learning training DBN is completed, the network is inversely fine-tuned in a supervised manner. The BP algorithm is simple and versatile, and has better fine-tuning effect in prediction. Therefore, the BP algorithm is used when training DBN. The training process is as follows: First, the input feature vector is propagated along the input end to the output; then the reverse is used. Propagation, calculating the error between the output of the BP network and the correct result, and propagating the error back from the input to the input to modify the weight and offset of the DBN’s neuron node. This paper uses the Sigmoid function as the evaluation function of the BP network node.

3.2 Brief introduction of Boltzmann machine

RBM is the core of the DBN network [20]. RBM is a probability map model that can be explained by a random neural network, which was proposed by Smolensky on the basis of the Boltzmann machine (BM) in 1986. The RBM consists of an input layer and an implicit layer. The connection mode of the neurons is that there is no connection within the layer and the layers are fully connected. The state of each neuron in RBM is divided into an active state and an inactive state. The structure of a single restricted Boltzmann machine is shown in Figure 6 below:

Figure 6. Restricted Boltzmann machine structure

$n_v, n_h$: Represents the number of neurons included in the visible and hidden layers, respectively;
$v = (v_1, v_2, ..., v_{n_v})^T$: The state vector of the visible layer, $v_i$ represents the state of the $i$-th neuron in the visible layer;
$h = (h_1, h_2, ..., h_{n_h})^T$: The state vector of the hidden layer, $h_j$ represents the state of the $j$-th neuron in the visible layer;
$a = (a_1, a_2, ..., a_{n_v})^T \in \mathbb{R}^{n_v}$: The offset vector of the visible layer, $a_i$ represents the state of the $i$-th neuron in the visible layer;
$b = (b_1, b_2, ..., b_{n_h})^T \in \mathbb{R}^{n_h}$: The offset vector of the hidden layer, $b_j$ represents the state of the $j$-th neuron in the hidden layer;
$W = (w_{i,j}) \in \mathbb{R}^{n_h \times n_v}$: A weight matrix between the hidden layer and the visible layer, $w_{i,j}$ represents the connection weight between the $i$-th neuron in the hidden layer and the $j$-th neuron in the visible layer.
During the RBM training process, when the visual layer dimension is too high, the training efficiency is extremely low and the training cannot be successfully performed. In 2002, Hinton proposed the CD (contrast divergence) algorithm [21] to effectively solve the problem of low efficiency of RBM training.

Due to the structural characteristics of RBM (no connection within the layer, full connection between layers), it can be known that when the state of the visible cell is given, the activation states of the hidden cells are conditionally independent. At this time, the activation probability of the \( j \)-th hidden unit is:

\[
P(h_j = 1|v, \theta) = \text{sigmoid}(b_j + \sum_{i=1}^{n_v} w_{j,i} v_i)
\]  

(1)

Similarly, when the state of the hidden cell is given, the activation states of the visible cells are conditionally independent. At this time, the activation probability of the \( i \)-th visible cell is:

\[
P(v_i = 1|h, \theta) = \text{sigmoid}(a_i + \sum_{j=1}^{n_h} w_{j,i} h_j)
\]  

(2)

At the beginning of the CD algorithm, the state of the visible cell is set to a training sample, and the activation state of all hidden layer cells is calculated using equation (1). After the activation state of all the hidden layer units is determined, the probability that the \( i \)-th visible unit \( v_i \) takes a value of 1 is determined according to the equation (2), thereby generating a reconstruction. Thus, when using the stochastic gradient ascent method to maximize the value of the log likelihood function on the training data, the update criteria for each parameter are:

\[
\Delta w_{ij} = \eta \left[ (v_i, h_j)_{\text{data}} - (v_i, h_j)_{\text{recon}} \right]
\]

\[
\Delta a_i = \eta \left[ (v_i)_{\text{data}} - (v_i)_{\text{recon}} \right]
\]

\[
\Delta b_j = \eta \left[ (h_j)_{\text{data}} - (h_j)_{\text{recon}} \right]
\]  

(3)

Where \( \eta \) represents the learning rate and \(( \cdot )_{\text{recon}} \) represents the distribution of the model definition after one-step reconstruction. The CD algorithm with \( k \) steps (abbreviated as CD – \( k \)) is described as follows:

The pseudo code for a complete RBM training algorithm is as follows:

**Step 1 Initialize**

(1) Given a set of training samples \( S \{ |S| = n_s \} \)

(2) Given training period \( J \), learning rate \( \eta \) and CD – \( k \) algorithm parameter \( k \)

(3) Specify the number of cells in the visible and hidden layers \( n_v, n_h \)

(4) Initialize the offset vector \( a, b \) and the weight matrix \( W \)

**Step 2 Training**

For \( \text{iter} = 1,2, \cdots, J \)

Do{

1) CallCD – \( k \) \(( k, S, \text{RBM}(W, a, b) ) : \Delta W, \Delta a, \Delta b \)

2) Refresh parameters: \( W = W + \eta \left( \frac{1}{n_s} \Delta W \right), a = a + \left( \frac{1}{n_s} \Delta a \right), b = b + \eta \left( \frac{1}{n_s} \Delta b \right) \)

3.3 DBN modelling process

The structure of DBN used in this paper is 18-20-20-3, which is an input layer, double hidden layer and one output layer. The activation function adopts sigmoid function, and the initial weight is random distribution \( N(0,0.1) \). Number, the hidden layer offset is set to 0, and the visible layer offset is set to zero. Using the learning rate with the momentum term, it is expressed as \( \theta = \rho \theta + \eta \frac{\partial \ln L_{\theta}}{\partial \theta} \), where \( \rho = 0.94, \eta = 0.9 \) using \( k = 1 \), which is a one-step CD algorithm. Since the weights obtained from unsupervised learning are ideal, there is no need to use regularization enhancement transfer functions. The DBN network structure is shown in Figure 7 below:
Using 10,000 sets of training data and 5000 sets of check data, Figure 8 shows the output data on the training set using the DBN modelling method, and Figure 9 shows the predicted output data of the test set using the DBN modelling method. Get a very satisfying result.

4. Comparative analysis of modelling results
In order to further prove the advantages of DBN in industrial modelling, this paper uses BP neural network to establish the same CFB coordinated control system model, and analyses the advantages and disadvantages of the two models by predicting image and RMSE.

4.1 BP neural network modelling
The BP neural network, which has been shown to be a single hidden layer, has the ability to approximate any nonlinear system under a wide range of conditions [22, 23]. Considering that the entire circulating fluidized bed boiler power generation coordinated control system is a dynamic, stable point changing process, a dynamic model should be established. Because the CFB boiler has large delay and hysteresis, in addition to the amount of coal, the amount of primary air, the size of the valve opening affects the bed temperature, output power and main air pressure, it should also add the output variable at the last moment, even the last time. Go to the input of the coordination system. The
method of expanding the input dimension of the network is used to increase the dynamics of the model and achieve the purpose of enhancing the training data. This paper uses a three-layer BP neural network structure of 18-50-3 with an input layer, an implicit layer and an output layer. The layer is connected by the weight, the threshold and the transfer function. The learning process consists of forward propagation and error back propagation. The hidden layer activation function uses the sigmoid function, and the output layer activation function uses the linear function.

The random number with the initial weight of \([-1, 1]\) is the same as the data of the DBN modelling, and the following results are obtained. Figure 10 shows the relationship between input and output on the training set, and Figure 11 shows the relationship between input and output on the check set. In the verification group, we can see that there are a lot of cases of misalignment and poor performance in terms of severe nonlinearity.

\[
\text{Figure 10. BP neural network training group} \quad \text{Figure 11. BP neural network check group}
\]

4.2 Comparative analysis
The comparison between the predicted and actual values of the check group by the two methods is better than the BP neural network based modelling method based on the DBN CFB coordinated control system modelling method. Because DBN adopts unsupervised learning, which is self-learning and self-organizing, it can extract the deep features of data better and has nonlinear dynamic characteristics, which can better establish the nonlinear dynamic model of the system. Table 1 shows the root mean square error (RMSE) of the output data for both methods.

|                         | Output Power | Main steam pressure | Bed temperature |
|-------------------------|--------------|---------------------|-----------------|
| **BP neural network**   |              |                     |                 |
| Training group          | 0.0781       | 0.0563              | 0.0344          |
| Validation group        | 0.1383       | 0.2874              | 0.0975          |
| **DBN**                 |              |                     |                 |
| Training group          | 0.03462      | 0.0296              | 0.0124          |
| Validation group        | 0.08764      | 0.1674              | 0.0638          |

By comparison, it can be seen that the DBN modelling method is superior to the BP neural network modelling method. This is because the DBN modelling method can extract features deeper and have a better representation of the eigenvalues. In the forward propagation process, the unsupervised layer-by-layer training method can better extract the characteristics of the input data itself, and in the back propagation process, use the supervised method to fine tune and further optimize the extracted feature values. Prevent overfitting so that the final prediction is closer to the actual value.
Sections should be numbered with a dot following the number and then separated by a single space:

5. Conclusion

This paper introduces the application of Deep Belief Network in the modelling of coordinated fluidized bed boiler coordinated control system, and uses the field data of 330MW circulating fluidized bed boiler of Inner Mongolia Jinghai Power Plant for the verification and testing of the model.

Modelling the CFB boiler coordinated control system with BP neural network can show good followability on the training set, but the output data prediction effect is not good on the test set. The results clearly demonstrate the limitations of BP neural networks for models of highly nonlinear dynamic systems. Using the same I/O data applied to the DBN model, the results demonstrate the superiority of DBN modelling techniques in power plant modelling. The validity of the model is evaluated by calculating the RMSE value. The iterative steps and training time are significantly better than the neural network modelling method. The overall results show that the DBN modelling method can well establish a 330WM circulating fluidized bed boiler coordinated control system, which can well indicate the dynamic characteristics of the system.

References

[1] Luo Z.Y, He H.Z, Wang Q.H, et al. Current status and development prospects of circulating fluidized bed boiler technology[J]. Journal of Power Engineering, 2004, 24(6): 761-767.
[2] Yue G.X, Lu J.F, Xu P et al. Development Status and Prospect Analysis of Circulating Fluidized Bed Combustion[J]. China Electric Power, 2016, 49(1): 1-13.
[3] Feng J.k, Yue G.X, Lu J.F. Circulating fluidized bed combustion boiler [M]. Beijing: Electric Power Industry Press, 2003
[4] Moldenhauer P, Rydén Ms, Mattisson T, et al. Chemical-looping combustion and chemical-looping reforming of kerosene in a circulating fluidized-bed 300 W laboratory reactor[J]. International Journal of Greenhouse Gas Control, 2012, 9 (9): 1-9.
[5] Luo Z.Y, Qi K.F, Ni M.J.A Comprehensive Mathematical Model for Combustion of Coal-fired Circulating Fluidized Bed[J].Journal of Engineering Thermophysics,1993(01):92-96.
[6] Ni W.D, Li Z. Modelling and Simulation of 220t/h Tsinghua Circulating Fluidized Bed Boiler[J]. Journal of Combustion Science and Technology, 1995(03): 219-225.
[7] Gao M.M , Yue G.X, Lei X.J, Liu J.Z, Zhang W.G, Chen F. Study on control system of 600MW supercritical circulating fluidized bed boiler[J].Proceedings of the CSEE,2014,34(35):6319-6328.
[8] Niu P.F. Application Research on Intelligent Control System of Combustion Process of Large Domestic Circulating Fluidized Bed Boiler[J]. Proceedings of the CSEE, 2000(12): 63-67+72.
[9] Hou Z.S, Xu J.X. Review and Prospect of Data Driven Control Theory and Method[J]. Acta Automatica Sinica, 2009, 35(06): 650-667.
[10] Ye H.W, Ni W.D, Li Z. Artificial Neural Network Method for Modelling of Coal-fired Circulating Fluidized Bed Boiler[J]. Journal of Tsinghua University(Science and Technology), 1997(02): 21-25.
[11] Zhang J, Niu P.F. Modelling of unit load system using wavelet neural network[J].Power Engineering,2006(06):836-840.
[12] Niu P.F, Gao L, Meng F.D, Chen Guilin, Zhang Jun. Adaptive fuzzy control of combustion system of circulating fluidized bed boiler based on neural network decoupling[J]. Chinese Journal of Scientific Instrument, 2011, 32(05): 1021-1025.
[13] Dong Z, Sun J, Zhang Y.Y, Han W. PSO-PID control of combustion-steam system in circulating fluidized bed boiler based on α-order inverse neural network decoupling[J].Power Engineering,2009,29(06): 549-553+564
[14] Ma, Monitoring the particle size in CFB using fuzzy neural network. United States: N. p., 1999.
[15] Reh L, Ye H. Neural networks for on-line prediction and optimization of circulating fluidized bed process steps [J]. Powder Technology, 2000, 111(1): 123-131.
[16] Wu J, Meng Q, Jing S, et al. The Application of BP Neural Network to Bed Temperature Control System of CFB Boiler [C]// International Workshop on Intelligent Systems and Applications. IEEE, 2009:1-4.
[17] Kang Z.X, Zhang X, Ma Y.G, Wang B.S. Dynamic Modelling of Bed Temperature Control Neural Network for Circulating Fluidized Bed Boiler[J].Boiler Technology,2006(S1):32-35
[18] Hinton G E.Salakhutdinov R R.Reducing the dimensionality of data with neural networks [J].Science,2006,313(5786) : 504-507
[19] Qiao J.F, Pan Guangyuan, Han Honggui. Design and Application of a Continuous Deep Belief Network[J].Acta Automatica Sinica,2015,41(12):2138-2146.
[20] Niu W.D. Principle of Steam Turbine in Power Plant [M]. China Electric Power Press, 2008.
[21] Hinton GE (2002) Training Products of Experts by Minimizing Contrastive Divergence. Neural Computation 14: 1771–180
[22] Chen T P, et.al. Approximation Capability in Cn by Multilayer Feedforward Networks and Related Problems. IEEE Trans.NN.1995, 6:57-58
[23] Cybenko G, Approximation by Superposition of Sigmoid Functions. Mathematics of Control, Signals and Systems, 1989. 2: 303-304