APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR IDENTIFICATION OF A MICRO-ALTERNATOR SYSTEM

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Abstract

The paper describes the application of artificial neural networks for identification using experimental data of a computer controlled micro-alternator system. Mathematical algorithms are described in detail and associated architectures of analog artificial neural networks are presented. The accuracy of the identified model is assessed by direct comparison between micro-alternator outputs and neural network identified model outputs.

1-Introduction

In recent years, artificial neural networks (ANNs) have attracted considerable attention as candidates for novel computational systems because of the variety of advantages that they offer over the conventional computational systems. Among those advantages, the ability to memorize, rapidity and robustness are the most profound and interesting properties, which have attracted attention in many fields [1]. In power systems, ANNs are rapidly gaining popularity among power system researchers. The number of ANN applications to electric power problems has increased dramatically in the last few years. A brief overview of ANN applications to various power system problems is presented in [2-8]. The application areas include security and contingency analysis, fault diagnosis, harmonic source monitoring and identification, alarm processing, load forecasting, state estimation, economical load dispatching, etc. The results have shown that ANNs have great potential in power system on-line and off-line applications.

In this paper, the ANNs are applied to identify linear models for a micro-alternator system. The system is treated as a multi-input/single output system. The accuracy of neural models is assessed by direct comparison between its outputs and system outputs.

2-System Configuration

Fig. 1 shows the micro-alternator system configuration of the University of Liverpool [9]. The system comprises a 3 kva micro-alternator connected to a laboratory busbar through a transmission line simulator. An analogue simulator represents a three-stage steam turbine with a single reheater and an electro-hydraulic governor with interceptor and governor valves.

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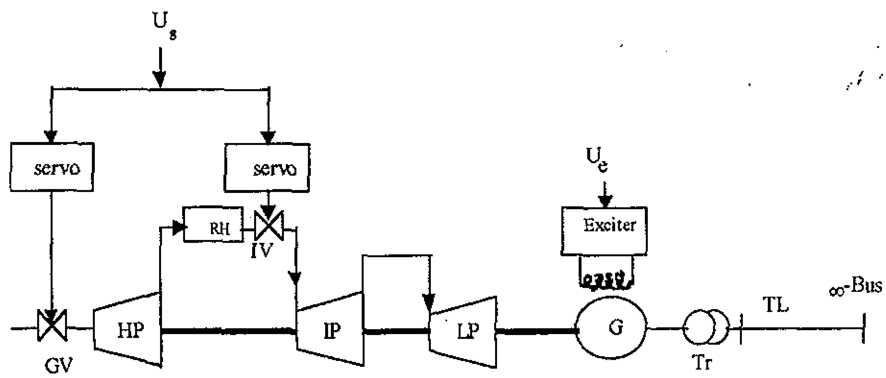


Fig. 1 System Configuration

3-ANN Architecture

In this paper we have used Multi Layer Feed Forward (MLFF) network with Back Propagation (BP) learning algorithm. In MLFF network the Processing Elements (PEs) are arranged in layers and only PEs in adjacent layers are connected. It has a minimum of three layers of PEs; (i) the input layer, (ii) the hidden layer, (iii) the output layer. The information propagation is only in the forward direction (input to output) and there are no feedback loops. A MLFF network topology is shown in Fig. 2. In order to obtain bounded output from PEs, a sigmoidal activation function is chosen where output is limited in the range from 0 to 1 for the input range from $-\infty$ to ∞. MLFF network is trained using back propagation (BP) algorithm. The BP algorithm adjust the weights using the relationship given below:

$$w_{ij}(new) = w_{ij}(old) + \eta\gamma_i o_j + \alpha(\Delta w_{ij}(old)) \quad (1)$$

where,

w_{ij} the weight from node i to node j

γ_i the error gradient at node i

γ_i for output layer neurons,

$$\gamma_i = (t_i - o_i)o_i(1 - o_i) \quad (2)$$

γ_i for hidden layer neurons,

$$\gamma_i = o_i(1 - o_i)\sum_{l=1}^{n_o} w_{li}\gamma_l \quad (3)$$

t_i = the target for i[th] output neuron
o_i = the output of i[th] neuron
n_o = the number of output neuron

η = the learning coefficient
= the momentum factor

During training, the actual patterns of the network in the final layer are compared with their target values for the given pattern. The aim is to minimize the square of the difference between the desired output (target) and the actual generalized output for the p-th pattern in the final layer.

$$E_p = \frac{1}{2} \sum_{i=1}^{n_o} (t_{ip} - o_{ip})^2 \qquad (4)$$

In order to ensure the stability of the BP algorithm, small values of α and η are used. But these results in slow learning requiring very large number of iterations for algorithm to converge. Higher values of α and η leads to faster learning but also results in oscillations.

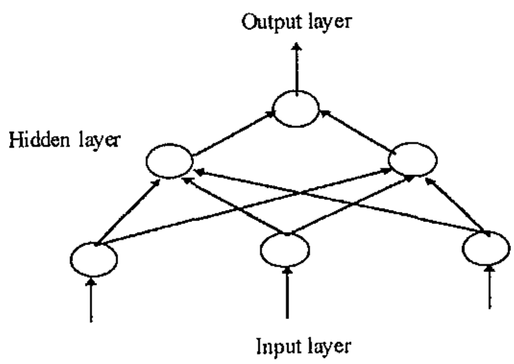


Fig.2 MLFF Network

4-Scaling of the Input and Output Data

The input and output variables for the neural network will have very different ranges and this may cause convergence problem during the learning process. To avoid this, the input and output data were scaled such that they were within the range (0,1), with majority of the data having values near to 0.5 (where the slope of the activation function is highest). For this purpose the actual input or output parameter was scaled using the following relationship.

$$X_s = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (5)$$

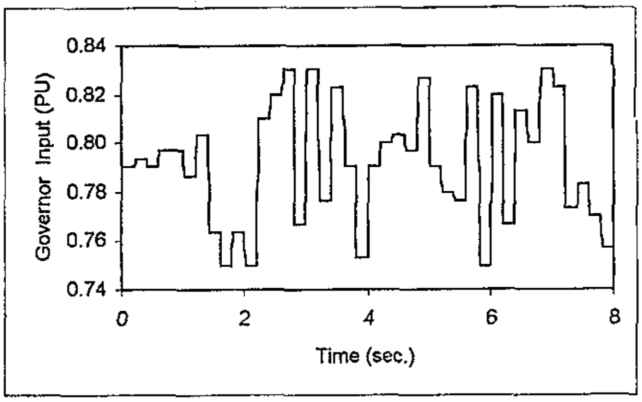
where,

X = actual data parameter
X_S = scaled data parameter which is used as input to the net.
X_{max} = maximum value of data parameter.
X_{min} = minimum value of data parameter.

5- System Identification
The neural networks can be extended to solve the identification problem which can be divided into the following three steps:

1. Model building,
2. The learning procedure (i.e. determination of model parameters),
3. Testing output reconstruction.

The experimental data for *identification have been obtained from the computer* controlled micro-alternator system of the University of Liverpool [9]. A sequence of random step signals updated every 0.2 second was imposed on the turbine governor and generator exciter inputs, in order to produce data for identification of the neural network models. Fig. 3 shows the inputs with random step signals.



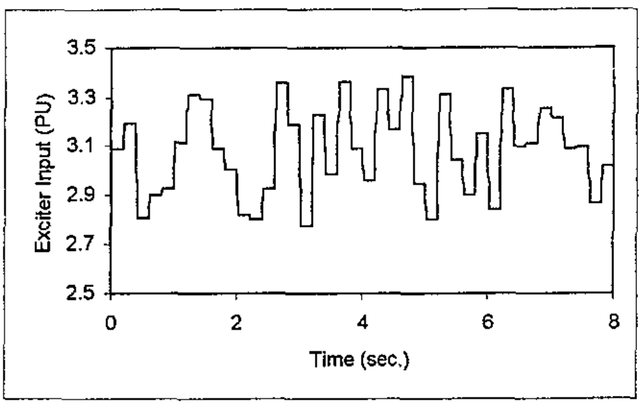
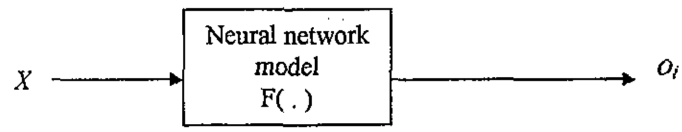


Fig. 3 Inputs with random step signals

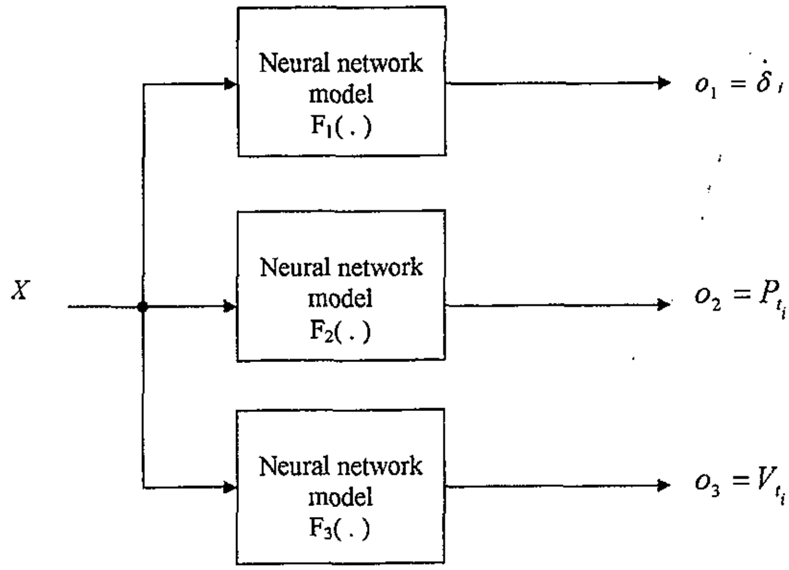
The outputs of the system are selected to be the rotor speed deviation $\dot{\delta}$, terminal power P_t, and terminal voltage V_t. The identification period is 8 seconds during *which 400 input/output data are collected* with a sampling interval of 20 millisecond. By using these data, suitable neural network models can be constructed. When these models are subjected to the same input u_i as the micro-alternator system, produce an output o_i which estimates the output t_i of the system in the sense that E_p is minimal. In this paper, two different neural network models are used. The first model shown in Fig. 4-a, the input vector X, is selected to be the governor and exciter inputs as well as three past values of the output. The single output o_i can be chosen $\dot{\delta}$ or P_t or V_t. So, the three outputs can be identified from three neural network models with different inputs. The second model shown in Fig.

4-b, the input vector, X contains the governor and exciter inputs as well as one past value of $\dot{\delta}$, three past values of P_t and three past values of V_t. The three outputs can be identified from three neural network models, which have the same inputs.



$$X = [o_{i-3}, o_{i-2}, o_{i-1}, u_{g_{i-1}}, u_{e_{i-1}}]$$

(a)



$$X = [\dot{\delta}_{i-1}, P_{t_{i-3}}, P_{t_{i-2}}, P_{t_{i-1}}, V_{t_{i-3}}, V_{t_{i-2}}, V_{t_{i-1}}, u_{g_{i-1}}, u_{e_{i-1}}]$$

(b)

Fig. 4 Different nonlinear neural network models
(multi-input/single-output system)

6-Simulation Results

The MLFF network used is a three layered feed forward architecture with one input layer, one output layer and one hidden layer of neurons. A separate ANN was trained for each output. As shown in Fig. 4-a, three ANNs were needed to identify the three outputs of the system. As the input data for each ANN consists of five variables, five neurons were used in the input layer. In Fig. 4-b, nine neurons were used in the input layer for each ANN. The output layer contains only one neuron to provide the identified model output. The convergence criterion is defined by the following average sum of square errors (ASSE):

$$ASSE = \frac{\sum_{p=1}^{N} E_p}{N} \qquad (6)$$

N is the number of output patterns in the final layer. Figures 5 and 6 show the ASSE against number of iterations for both five-input and nine-input neural network models with ten hidden layer neurons. It is clear that the ASSE decreases when the number of iterations increases. After eighty iterations, ASSE was calculated for each output and given as follows:

For five-input neural model

ASSE = 0.0000152 for terminal voltage
ASSE = 0.000143 for terminal power
ASSE = 0.000801 for rotor speed deviation

For nine-input neural model

ASSE = 0.0000145 for terminal voltage
ASSE = 0.0000625 for terminal power
ASSE = 0.000933 for rotor speed deviation

To increase the accuracy of both five-input and nine-input neural network models, ASSE is selected as:

ASSE $\leq$ 0.0000025 for terminal voltage
ASSE $\leq$ 0.000015 for terminal power
ASSE $\leq$ 0.00075 for rotor speed deviation

The optimum number of hidden layer neurons was found by trial and error. The training conditions of the three different feedforward neural networks are summarized in Tables 1 and 2. It is observed that the optimum number of hidden layer neurons is different for the three ANNs. Best convergence was obtained when the number of hidden layer neurons equals 6, 10 and 10 for training the three five-input ANNs, and 8, 8 and 10 for training the three nine-input ANNs, respectively.

Table 1
Three five-input ANNs performance with different number of hidden layer neurons

Q	OUTPUT No. 1 $\dot{\delta}$		OUTPUT No. 2 P_t		OUTPUT No. 3 V_t	
	Itr	SD	Itr	SD	Itr	SD
6	4176	0.035120	10384	0.005644	30022	0.002594
8	5329	0.035676	7842	0.006584	25791	0.002577
10	10964	0.035492	4749	0.006527	19719	0.002473

Table 2
Three nine-input ANNs performance with different number of hidden layer neurons

Q	OUTPUT No. 1 $\dot{\delta}$		OUTPUT No. 2 P_t		OUTPUT No. 3 V_t	
	Itr	SD	Itr	SD	Itr	SD
6	43440	0.036504	13388	0.004536	67769	0.003134
8	36619	0.037179	8383	0.004695	51315	0.003082
10	58612	0.037419	10611	0.004780	36911	0.003132

Note: Q is the number of hidden layer neurons, Itr is the number of iterations and SD is the standard deviation.

Figures 7 and 8 show comparisons between the micro-alternator outputs and ANN model outputs when the number of hidden layer neurons equals 10. A close agreement is observed between the micro-alternator and ANN model outputs. These results are very important because the ANN models can be used in the adaptive controller design.

7- Conclusion

The paper presents a new application of ANNs for identification of linear models for a micro- alternator system using input/output experimental data. The effect of number of hidden layer neurons on both ANN model accuracy and number of iterations for convergence has been studied. The accuracy of neural models was assessed by direct comparison between its outputs and alternator outputs for the same inputs. From the simulation results, a close agreement was observed between the system and ANN model outputs which illustrate the validity and performance of the described ANN algorithms.

8- Acknowledgment

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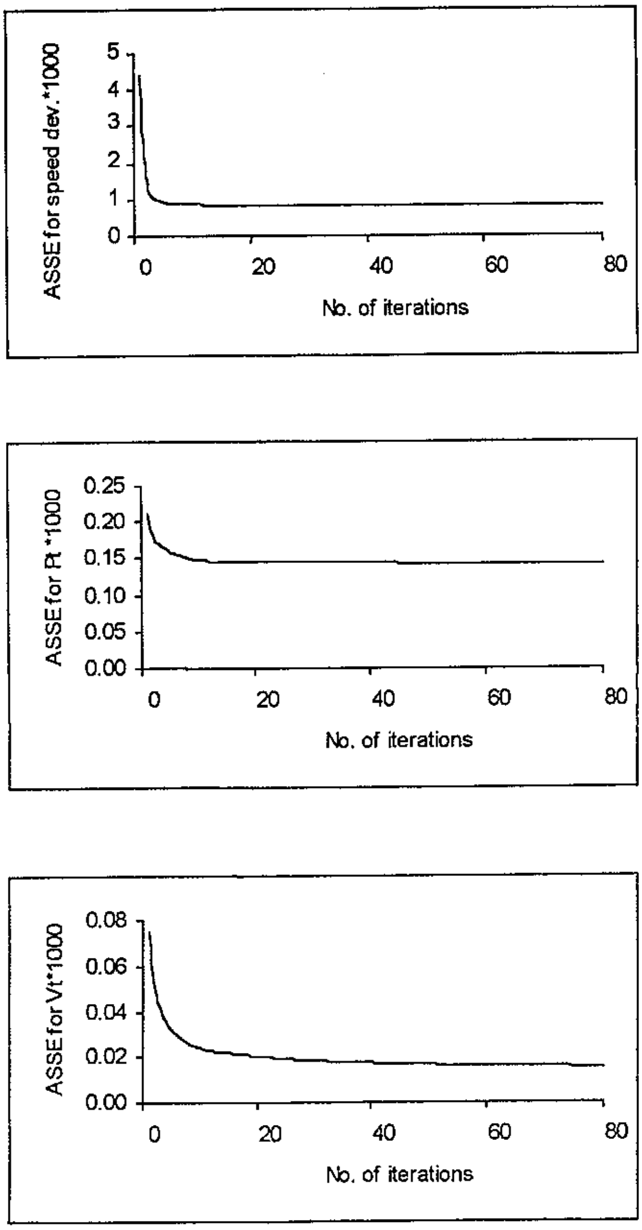


Figure 5 ASSE against number of iterations for five-input neural network models.

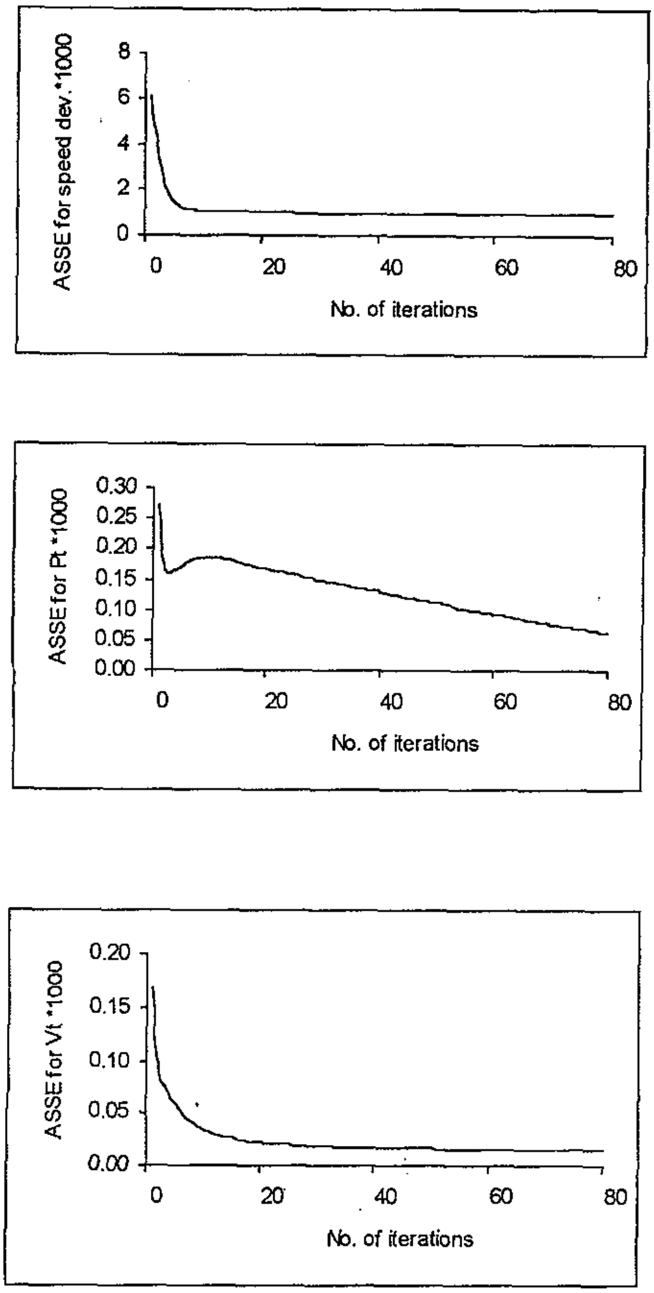
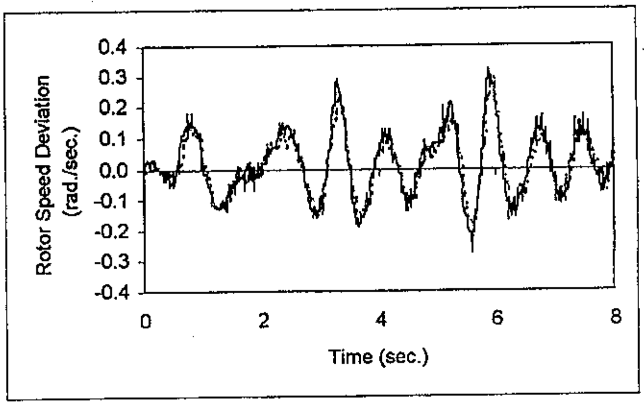
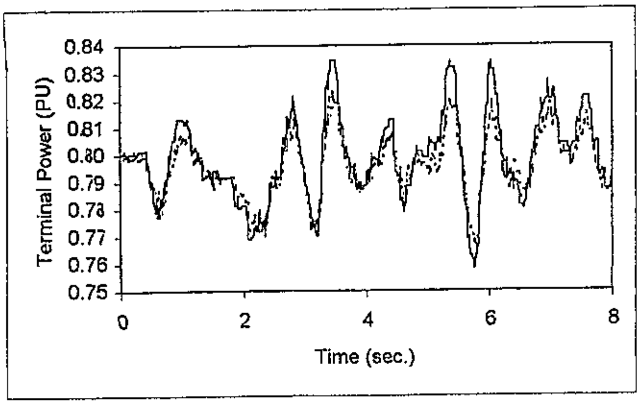


Figure 6 ASSE against number of iterations for nine-input neural network models.



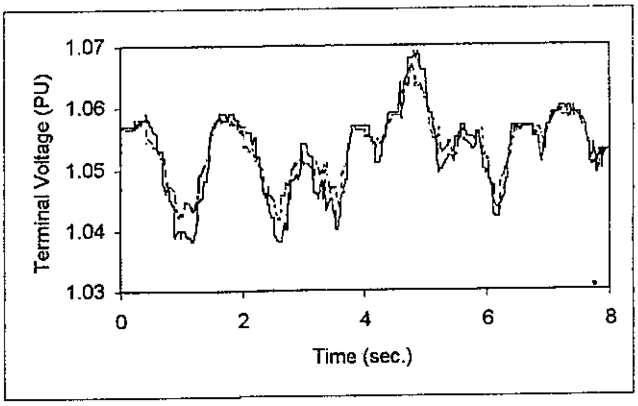
$$X = [\dot{\delta}_{i-3}, \dot{\delta}_{i-2}, \dot{\delta}_{i-1}, u_{g_{i-1}}, u_{e_{i-1}}]$$

(a)



$$X = [P_{t_{i-3}}, P_{t_{i-2}}, P_{t_{i-1}}, u_{g_{i-1}}, u_{e_{i-1}}]$$

(b)



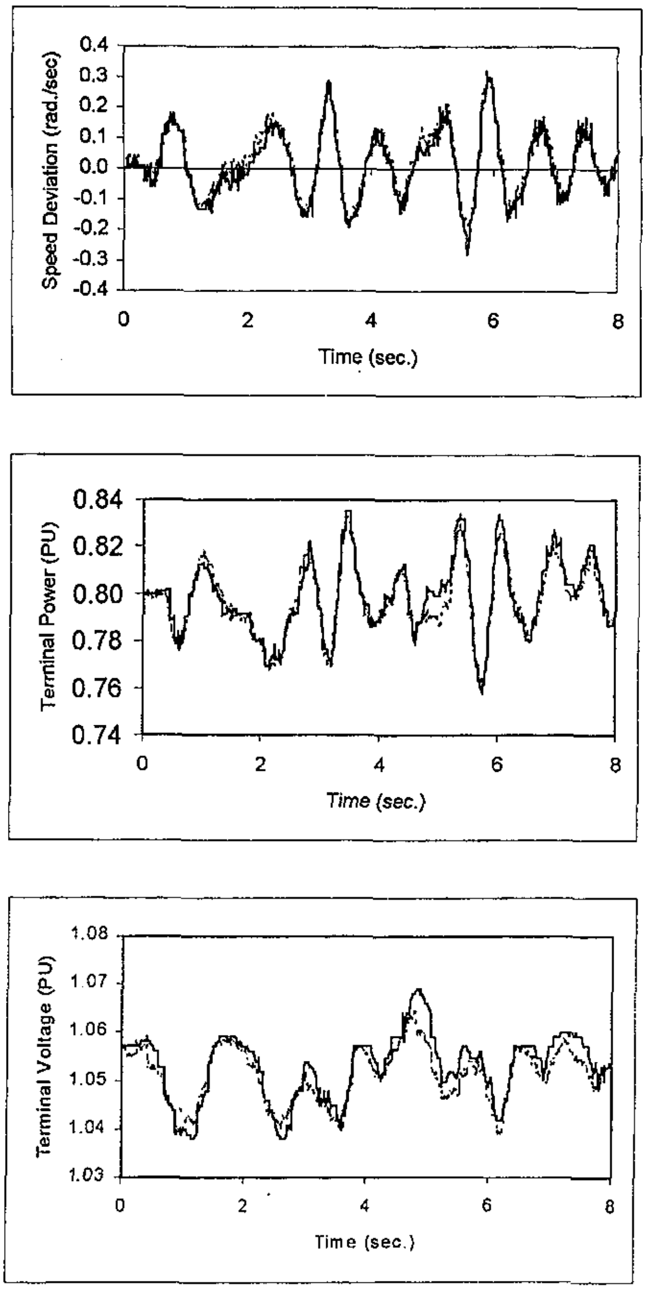
$$X = [V_{t_{i-3}}, V_{t_{i-2}}, V_{t_{i-1}}, u_{g_{i-1}}, u_{e_{i-1}}]$$

(c)

Fig. 7 Comparison between micro-alternator outputs and five-input neural network models outputs.

----- ANN model output

—— Micro-alternator output



$$X = [\delta_{i-1}, P_{t_{i-3}}, P_{t_{i-2}}, P_{t_{i-1}}, V_{t_{i-3}}, V_{t_{i-2}}, V_{t_{i-1}}, u_{g_{i-1}}, u_{e_{i-1}}]$$

Figure 8 Comparison between micro-alternator outputs and nine-input neural network models outputs.

----- ANN model output

___ Micro-alternator output

تطبيق الشبكات العصبية الاصطناعية فى استخلاص نماذج لنظام مولد تزامنى صغير

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يقدم البحث تطبيق جديد لإستخدام الشبكات العصبية الاصطناعية فى استخلاص نماذج خطية لنظام مولد تزامنى صغير. التطبيق يعتمد على قراءات معملية لدخل وخرج النظام. إقترح البحث نموذجين للنظام تم إستنتاجهما من هذه القراءات باستخدام الشبكات العصبية الإصطناعية. النموذج الأول له خمسة دخول وخرج واحد بينما النموذج الثانى له تسعة دخول وخرج واحد. تم قياس دقة هذه النماذج عن طريق:

- مقارنة خروجها مباشرة بنظائرها من النتائج العملية.
- حساب الإنحراف المعيارى لكل خرج.
- حساب متوسط مجموع مربعات الأخطاء لكل خرج.

تم دراسة تأثير عدد الخلايا العصبية فى الطبقة المختفية على دقة النماذج المستنتجة. أظهرت النتائج مدى دقة النماذج المستنتجة باستخدام الشبكات العصبية الاصطناعية مما يمثل أهمية كبيرة فى إمكانية استخدام هذه النماذج فى تصميم الحاكمات التكيفية.