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Different Structures of Neural Networks Training by Genetic Algorithm for Nonlinear System

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***Abstract*— In this paper, Artificial neural network training by genetic algorithm is applied to modeling the governor-turbine system using a big system test data. Three different data sets are used for training, testing and validation. The validation data used to stop GA training to prevent data over fitting. The studied system is a standard nonlinear thermal device implemented for stabilizing the system frequency due to load changes. Genetic algorithm is used to finding the optimum values for the weights and bias matrix of the fixed structure neural network, which provide the minimum error. Varying the model of the network can be fulfill by affecting the connections between neurons and the number of hidden layers. Different number of hidden layers with the same number of neurons are applied to determine the best structure for governor control problem. A comparative study is used for different neural network structures using mean square error and the time of optimization to achieve the best hidden layer frame. The studied system is represented by a set of nonlinear differential and algebraic equations. MATLAB software is implemented for solving the proposed system equations.**

Keywords— genetic algorithm; artificial neural network; governor control; hidden layer arrangement

I. Introduction

Many researchers with a good potential in finding the resolution of the case that, determining the required number of neurons to be fixed in the hidden layer for providing good response, but so far, no promising formula is developed for determining the number of neurons in the hidden layer for minimizing the training time required for the neural network with sufficient increase in the accuracy in determining target output.

Training data for standard well known problems using back propagation neural network with Multiscript pin code recognition system in [1], was analyze the number of neurons in the input layer. The author made an approach in order to save the fineness as a general criterion. The implementation of two-layer neural network results in improving the fineness with 95%.

The hidden layers of the network usually affect the neural network performance. The procedures of reporting the configuration of hidden layers are one of the major problems facing researchers [2-3].

When the fineness is the factor and no limit for the training time is mentioned multiple hidden layers are used. For optimization process the disadvantages of implementing multiple hidden layers in the neural network is that they are more permission to fall in bad local minima [4].

There great effort has been done to improve the performance of neural network based genetic algorithm approach [5-10].

Particle swarm optimization (PSO) technique has incorporated with genetic algorithm (GA) to form Hybrid model called HPSOGA for defining the parameters of the radial basis function neural network (RBFNN) to enhance the global system performance [5]. The model explored based on the HPSOGA is a promising model for providing fineness prophesy and best generalization ability. Feedforward and recurrent neural network have been developed based on a fast-learning neuroevolutionary algorithm. The neuroevolutionary algorithm has been inspired by Cartesian genetic programming (CGP). The technique leads to strong evolutionary search for prospect topologies [6]. The genetic algorithm GA has been applied successfully for training feedforward neural network for distinguish the involvement effectively. The normal and abnormal connections have been classified using the obtained parameters, the fineness of the model [7]. The genetic Algorithm (GA) approach has been implemented for training and pruning the neural network. Extinction and immigration operator have been applied successfully for training the neural network and providing very good results [8]. The Non-dominated Sorting Genetic Algorithm (NSGA-II) has been incorporated into neural network (NN) structure to form a data driven model for solving the optimization process of determining the effective factors from multi-objective optimization. The technique has been applied to determine the effective factors of traffic crashes [9]. Multi objective genetic technique to extract knowledge from trained artificial neural network based on implementing association rules technique. The objective of such hybridization is to extract optimal rules from the neural network for further classification [10].

The application of NN based genetic algorithm take place in many industrial fields [11-20]. Identifying variable mass underwater vehicle (VMUV) with six degree of freedom model has been developed using implementation of neural network and genetic algorithm [11]. Volterra neural network is combined with genetic algorithm to form the structure of the nonlinear polynomials. Prophesy the fuel consumption for space shuttle is an important factor for minimizing the harmful effects of fuel emissions, decreasing the fuel energy exporter, decreasing flight price, providing accurate space-shuttle trajectory prophesy, and achieving active and seamless management of space shuttle. The genetic algorithm is implemented for optimizing the neural net

work model for prophesy fuel flow rate of aircraft based actual flight data [12]. Enhancing the prophesy fineness of the short-term traffic flow rate, hybrid model based on clustering search strategy genetic algorithm and wavelet neural network model has designed. The genetic algorithm is applied for optimizing the initial connection weights, translation factor, and scaling factor of wavelet neural network. The experimental results show that this model provide high fineness and best nonlinear fitting ability in compared with the traditional model [13]. The preparation process of membrane has been successfully investigated by implementing artificial neural network. The optimum concentricity for providing maximum flux for fourfold system have been prophesy using genetic algorithm. An agreement experimental and calculated data have been investigated [14]. The genetic algorithm (GA) has been incorporated with artificial neural network for solving sophisticated problems. A modified model implementing ANN and GA has been implementing for determine the optimum parameters of the biogas production from waste digester [15]. The developed model provides better results. The back-propagation network, (BPN) has been incorporated into genetic algorithm (GA), to form hybrid model for estimating the nanofluid density. This model has been applied successfully to optimize the parameters of the BPN's, and enhance the fineness of the hybrid model [16]. The obtained results from such model have an excellent agreement with the experimental results. The neural network and genetic algorithm optimization have been applied to design an industrial roof. To ensure such accurate model based on this technique different loading conditions, and different trusses have been considered. The

stress and displacement constraints for the previous cases also have been considered [17]. The artificial neural network has been applied to define the logical interaction among dependent and independent parameters and define cost function of Savonius rotor. The deduced function from neural network is optimized by implementing genetic algorithm for each parameter [18]. A constraint based genetic algorithm (GA) to determine 2-hidden layer network for predicting loss of coolant accident (LOCA) of nuclear power plant (NPP). The GA has been used for creating an initial population of neural network architectures with high performance [19]. The artificial neural network (ANN) has been applied to prophesy the effects of operational parameters on the dissolution of Cu, Mo, and Re from Molybdenite concentrate during meso-acidophilic bioleaching. The genetic algorithm (GA) has been applied to determine the optimum parameter for the best model defined by ANN [20]. The NN based GA have applied successfully in the field of medical and social field [21-25]. Genetic algorithms (GA) have been incorporated into deep convolutional neural network (CNN) to predict the human action. The weights of the CNN classifier have been initializing by means of GA, in order to minimizes the classification error, and improve the model performance [21]. Genetically optimized neural network (GONN) has been developed for classifying breast cancer diagnosis [22]. This will be providing a large benefit for early detection and suitable treatment for decreasing the breast cancer death-rate. The ionospheric total electron content (TEC) over China has been prophesy via a developed neural network (NN) approach. The genetic algorithm (GA) has been implemented to avoid local minimum caused by conventional NN. The obtained results showed that the GA-NN model is a powerful and flexible tool in the ionospheric studies [23].

In this paper, Artificial neural network training by genetic algorithm is applied to modeling the governor-turbine system represented by [26], using a big system test data. The study unit is a standard nonlinear thermal unit utilized for the load-frequency regulation.

Genetic algorithm is used to finding each connection weights and biases of a fixed structure neural network, which provide the minimum error. Changing the structure can be accomplished by manipulating the connections between neurons and the number of hidden layers.

Different number of hidden layers with the same number of neurons are applied to determine the best structure for governor control problem.

I. MATERIALS AND METHOD

Multi-layer neural networks, the first layer is called the input layer, the last layer is called the output layer, and there are several hidden layers come in between [27].

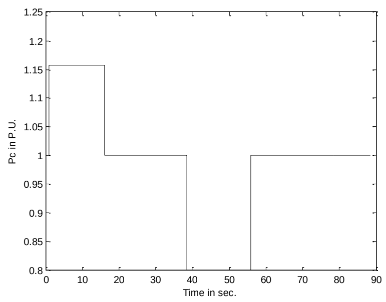

Fig. 1. **Mechanical power disturbance signal for training governor system**

The proposed test system is calculated through the time domain simulations. The sample data is generated with double step variation in the two direction of the input mechanical power, as shown in Fig. 1. The test data are rotor angle and generator speed with two-time delay for each one of them, are select as a feature. This gives a six input training data. For 0.005-time step, that generate 17701 data point during training. The collected data is divided into training data set with 70% testing and validation subsets with 15% of the total data.

The Genetic Algorithm (GA) was developed by the evolutionary theory of Darwin. This function should decrease mean square error to minimum value. The genetic algorithm is usually implemented for searching the optimum bias and weights parameters of the network. The system output error is obtained by square the difference between target output and actual output. The optimization algorithms implementation to train neural network, all network parameters are converted into a single vector.

A series of 20 chromosomes is created randomly and then the control parameters are encoded. Fitness function is developed to generate more resistant generations using operators of 0.8 crossovers, 0.5 selection factor in each iteration step. For maximum generation 100 the fitness limit used is 10^{-8}.

The validation data used to stop GA training to prevent data over fitting. Therefore, the best validation occurs and there is no significant over fitting.

The tolerance obtained during training as an objective function for GA to be minimized is obtained from squaring the deviation between the real output and target.

II. Results And Discussions

Three case study for single, double and three hidden layers, under the same number of neurons (equal 7 neurons plus one for the output layer) in a hidden layer was used to achieved the performance of the ANN.

Case 1. Single hidden layer

The structure of the neural network used is (7-1), means seven neurons in a single hidden layer with one neuron for the single output (governor output). The convergence characteristic of GA clearer in Fig.2

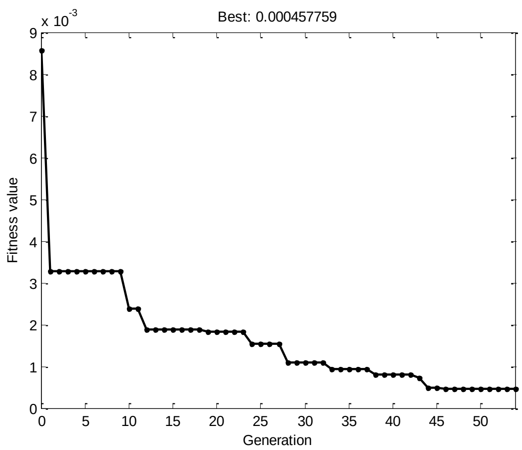

Fig. 2. **The convergence characteristic of GA for Case 1.**

The control parameter of GA obtained the weights between the (input-hidden-output) layers and biases of each neuron for the a fixed structure neural network are obtained in Table I.

Case 2. Two hidden layer

The structure of the neural network used is (3-4-1), means two hidden layer with three neurons in the first and for in second hidden layer. The convergence characteristic of GA obtained the best performance during iterations Fig. 3

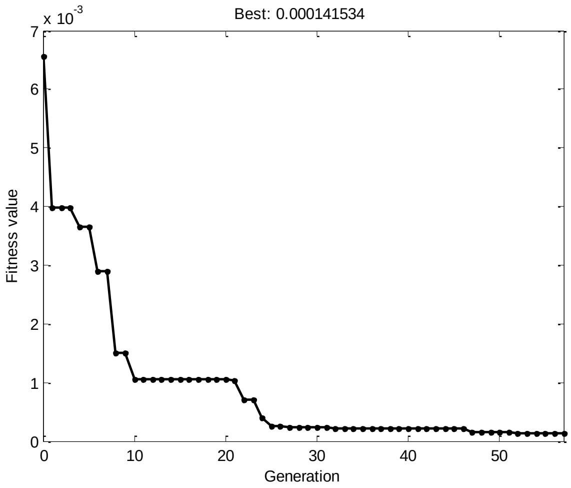

Fig. 3. **The convergence characteristic of GA for Case 2.**

The GA control parameters for (input-2hidden-output) layers are illustrated in Table II.

Case 3. Three hidden layers

In this case for the need to maintain a fixed number of neurons for fairly judgment, the structure of the neural network used is (2-4-1-1), means three hidden layers. The convergence characteristic of GA obtained the best performance during iterations Fig. 4

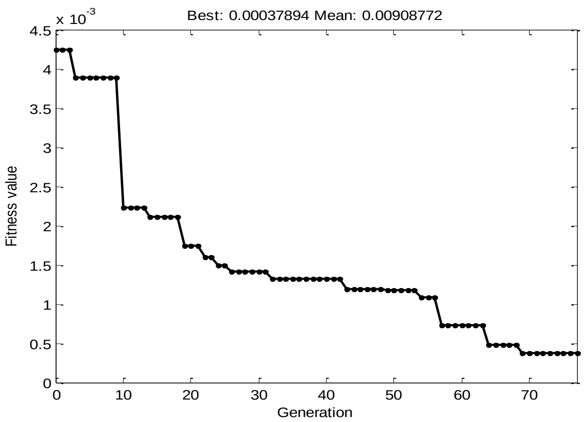

Fig. 4. **The convergence characteristic of GA for Case 3.**

TABLE I. **RESULTS OBTAINED BY GA-ANN CASE 1.**

Biases		**Input weights**						**Layers weights**
L1	***O***	***I1***	***I2***	***I3***	***I4***	***I5***	***I6***	***L1-O***
0.5556	**1.0534**	**-1.3287**	**0.3149**	**0.6116**	**0.7647**	**1.0791**	**0.158**	**1.0699**
0.7162		**0.2771**	**0.7189**	**-0.4282**	**-0.237**	**0.1001**	**1.0409**	**0.0782**
1.5696		**2.0071**	**0.7053**	**0.3477**	**1.0566**	**1.1834**	**0.2114**	**0.6052**
0.3897		**0.43498**	**0.3389**	**0.41899**	**2.916**	**0.13098**	**0.2499**	**0.1551**
-0.4789		**-0.26797**	**0.2067**	**1.8913**	**0.0761**	**0.1779**	**0.4377**	**0.126**
0.6359		**0.8894**	**1.0319**	**0.1537**	**0.6043**	**0.46978**	**-0.0689**	**-0.878**
0.5028		**0.84353**	**0.6087**	**-0.6263**	**0.3636**	**-0.4789**	**1.4107**	**0.8887**

TABLE II. **RESULTS OBTAINED BY GA-ANN CASE 3.**

Biases			**Input weights**						**Layers weights**			
L1	***L2***	***O***	***I1***	***I2***	***I3***	***I4***	***I5***	***I6***	***L1- L2***			***L2-O***
0.6179	**0.1373**	**0.0765**	**0.4808**	**0.8739**	**0.0051**	**-0.3988**	**0.3353**	**0.70412**	**0.1212**	**0.7993**	**0.1904**	**0.5313**
0.6866	**0.223**		**0.8067**	**-1.3652**	**0.4095**	**1.1823**	**0.9508**	**-0.1276**	**0.3683**	**0.6882**	**0.8477**	**0.7009**
0.1545	**0.763**		**-0.2367**	**0.862**	**0.81767**	**1.3557**	**0.16748**	**0.36427**	**0.0007**	**0.5359**	**0.0213**	**0.3959**
	1.5062								**-0.149**	**0.1446**	**0.3125**	**-0.347**

TABLE III. **RESULTS OBTAINED BY GA-ANN CASE 3.**

Biases				**Input weights**						**Layers weights**			
L1	***L2***	***L3***	***O***	***I1***	***I2***	***I3***	***I4***	***I5***	***I6***	***L1- L2***		***L2-L3***	***L3-O***
0.7650	**0.74354**	**0.1688**	**-0.0777**	**0.91094**	**-0.6317**	**-0.6435**	**0.3399**	**0.6487**	**0.9058**	**1.2306**	**-0.1173**	**1.1382**	**1.01995**
1.01343	**-0.0234**			**-0.3495**	**0.7135**	**0.9954**	**0.8839**	**0.6979**	**0.8423**	**-1.0125**	**1.8252**	**0.6725**	
	2.0717									**2.5372**	**0.1736**	**1.4313**	
	0.1103									**0.3559**	**0.9268**	**1.43123**	

TABLE IV. **COMPARISON OF NETWORK PERFORMANCE WITH DIFFERENT NUMBERS OF HIDDEN LAYER**

Cases	**Optimization time**	**MSE**	**GA iterations**	**No. of hidden layers**	**No. of neurons**	**No. of control parameters**
Case 1	**35.718 s**	**0.0004578**	**54**	**1**	**8**	**57**
Case 2	**45.116 s**	**0.0001415**	**57**	**2**	**8**	**42**
Case 3	**65.0809 s**	**0.00037894**	**77**	**3**	**8**	**33**

The total control parameters for (input-3 hidden-output) neural network layers in Table III.

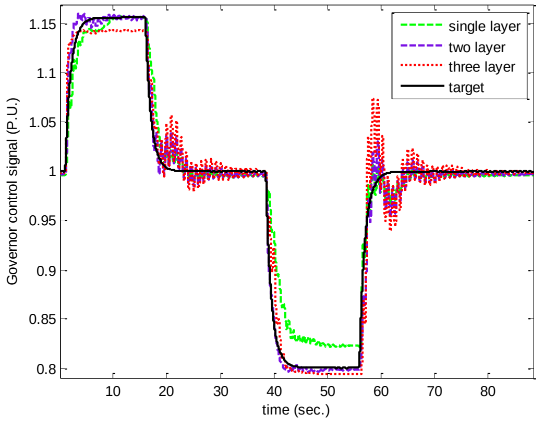

Fig. 5. **Comparative performances of the governor output estimated by GA-ANN Model**

The mean square error, training time, number of GA control parameters and the training iteration until reach the optimal solution, that can be seen from Table IV.

Comparative performances of all cases under study to for the prediction the governor model are clarified in Fig. 5

III. CONCLUSION

In this work several artificial neural network structures are used to model the governor-turbine system. Different structure arrangement with the same number of neurons is applied to determine the best structure for governor control problem. A big number of data is used for training, testing and validation the result system. The tested data has obtained from a standard high order nonlinear single machine infinite bus system with a slandered thermal unit that implemented for the frequency stabilizer regulation.

Genetic algorithm is used to finding each connection weights and biases of the neural network, which provide the minimum mean square error as a fitness.

By increasing the number of hidden layers, the complexity of the neural network and training time has linear increase. However, if the fineness is the major factor for developing the NN model then hidden layers will well with nonlinear way. The mean square error achieved best a great extend for two-layer system.

Finally, a simulation result is provided to verify the effectiveness of the proposed training mechanism and neural network structure in improving the performance of the studied system.

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