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Effective Identification of a Turbogenerator in a SMIB Power System Using Fuzzy Neural Networks

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***Abstract*—This paper presents modelling and identification of a turbogenerator in a single-machine-infinite-bus (SMIB) power grid utilizing Fuzzy Neural Networks (FuNNs) to construct an online adaptive identifier for the turbogenerator. It is well known that a turbogenerator is a highly nonlinear, fast acting and multivariable system usually connected to a power system. When major power system disturbances occur, protection and control actions are required to stop power system instability and restore the system to a normal state by minimizing the impact of the disturbance. Therefore, effective intelligent techniques are required to model and identify such a complex system. In this paper, a FuNN identifier (FuNNI) of a turbogenerator model is proposed. Computer simulations are carried out to investigate the modelling after deriving the mathematical model of the turbogenerator equipped with a conventional turbine governor and automatic voltage regulator (AVR). Inverse identification scheme is adopted using a multi-input multi-output (MIMO) fuzzy neural network. Empirical results show that the proposed FuNNI is capable of successfully identifying a highly nonlinear turbogenerator system and robust even when the configurations of the plant change due to faults in the power system.**

***Keywords*—Turbogenerator, Fuzzy Neural Networks, adaptive identification, single-machine-infinite-bus, power systems.**

I. Introduction

THE electric power has steadily increased in recent years that became an important part of a daily modern life. It is expected to meet the rising demand, and the power system will grow in size as more generating plants of larger capacity are built in remote areas. A Fossil Fuel Power Unit (FFPU) supplies electric power as the result of a series of energy conversion processes. Briefly, the main transformations include combustion of input fuel, steam generation, development of rotational motion, electric power production and steam condensation. All these transformations compose a large thermodynamic cycle and are highly interdependent [1]. Turbine and generator, hence called Turbogenerator (TG), are two main parts of a power plant and involve the control valve of steam flow on the turbine side as well as excitation system on the generator side. An extremely important feature of a turbogenerator is the dynamic link between the turbine and the generator which is usually connected to a transmission line simulated by an infinite bus [2]. The complete system involves a highly nonlinear system which requires an efficient techniques to build an effective identification for an accurate modelling [3]. The past decade has witnessed a growing body of experimental work and studies on turbogenerators. Mayouf *et al.* [4] studied the effect of the implementation of power system stabilizers (PSSs) into the excitation system as well as the turbine governor to enhance damping of power system oscillations for single-machine-infinite-bus (SMIB) power system. Huo *et al.* [5] performed numerical calculations of a 3-D nonlinear transient eddy current model of a turbogenerator. Furthermore, Venayagamoorthy, *et al.* [6] implemented a continuously online trained artificial neural network (ANN) controller to identify the continuous changing complex nonlinear dynamics of the TG which consists of a turbine simulator and a micro-alternator in a laboratory environment. The study has shown that the ANN identifier/controller has the potential to augment/replace the automatic voltage regulator (AVR) and the turbine governor and to allow the TG to operate more closely to their steady state stability limits.

Nonlinear auto-regressive moving average with exogenous inputs (NARMAX) [7] is a widely used model to identify nonlinear models. However, it usually needs numerous coefficient to estimate, and the estimation is a complex process [8]. Generally, there are two types of system identification schemes, namely, the forward dynamics identification and the inverse dynamics identification [9]. Park *et al.* [10] compared MLP and RBF neural network forward identifiers as two neurocontrollers of the turbogenerator. Qinghong *et al.* [11], proposed an online learning algorithm of the artificial neural network (ANN) inversion with online gradient descent method based on offline training for two-machine power system. Moreover, Sambariya and Prasad [12] presented a fuzzy logic power system stabilizer to enhance damping of SMIB system. The speed deviation and acceleration are taken as the only inputs to the fuzzy logic controller due to the effectiveness of these variables on damping at the generator shaft mechanical oscillations.

In this paper, a fuzzy neural network model is proposed

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to identify the continuous changing nonlinear dynamics of the turbogenerator. An inverse online adaptive identification scheme is adopted such that the parameters of the FuNN (centers, width and output weights) are updated continuously after each input-output training pairs. The inverse identifier has the advantages that it can then be used as a forward controller for the TG plant without the need of extra efforts in learning the controller.

The rest of this paper is organized as the following. A mathematical model of the turbogenerator plant is presented in section II followed by development of computer simulations of the derived model under conventional controllers. In section III, the FuNN architecture is described. Training algorithm enhanced by learning equations is also given. Section IV gives the proposed fuzzy neural model and the scheme for identifying the turbogenerator plant. Finally, conclusions and future work are presented in section V.

II. Dynamic Model Simulation of a Turbogenerator

A single-machine-infinite-bus (SMIB) power system is shown in Fig. 1. This system consists of a turbogenerator connected to an infinite bus through transmission lines. The TG is equipped with a traditional AVR and a turbine governor.

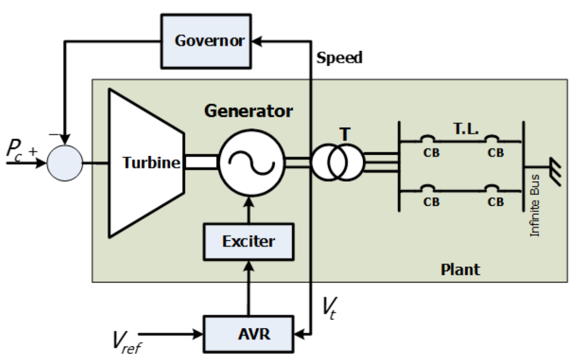


Fig. 1: A single-machine-infinite-bus with traditional control.

A. Steam Turbine and Control Valve Model

Assuming a boiler control that provides constant steam pressure and temperature to the inlet of the turbine control valves, the turbine power can be expressed as a function of only the valve opening. The control valve model represents main and interceptor valves being governed in parallel to give a fast response [13]. The turbine governing system dynamics including governor valve, high-pressure (HP) turbine, reheater and intermediate pressure/low pressure (IP/LP) turbine are represented as a first order lag element [13], and is given as follows

$$\dot{P}_m = \frac{-P_m}{T_T} + \frac{K_T}{T_T} X_E \tag{1a}$$

$$\dot{X}_E = \frac{-X_E}{T_G} + \frac{U_g}{T_G} \tag{1b}$$

where: T_T: Turbine time constant, T_G: Control valve time constant, U_g: Control input for governing system, P_m in per unit (p.u.): Turbine mechanical power, K_T: Turbine gain. And the following practical constraint is placed on the valve opening X_E: $0 \leq X_E \leq 1$.

B. Conventional Governor Control

The speed deviation (power change) signal is detected by the speed governor which converts it into an appropriate valve action. The basic control element in Electro-Hydraulic Control (EHC) is the hydraulic servo that produces a steady state output U_g, directly proportional to the desired steady state turbine power output [14]. The inputs to the speed control are speed error $\Delta\omega$ and the load reference P_c:

$$U_g = P_c - \frac{\Delta\omega}{R\omega_o} - P_e \tag{2}$$

where: P_c: Reference of power (p.u.), P_e: the active power of the generator (p.u.), $\Delta\omega$: Speed deviation (rad/sec), ω_o: Rated speed (rad/sec), R: Speed regulation. R is 5%, which signifies that for a 5% change in system frequency (2.5 Hz), the valves will move 100% [15].

C. Electrical System Model

The electrical system model comprises an electric power system model, a generator model and an excitation system model. The electric system model receives information on the turbine power from the turbine model, resolves a swing equation that uses the difference between the turbine power and electrical power output from the generator, and feeds the obtained speed to the turbine model.

1) Electric Power System Model: The power system is modelled as a one machine connected to an infinite power bus through a step up transformer (T) and two parallel transmission line (T.L.) groups with circuit breakers (CB) as shown in Fig. 1.

2) Generator Model: One of the most important apparatus which must be modelled in a power system transient or dynamic stability is the generator. The generator model is expressed by Parks $d-q$ two axes model [16] which consists of mechanical and electrical systems:

- *Mechanical System Equations of the Generator:* When the system is in a transient, some changes occur to mechanical parts such as the shaft of the coupled turbine-generator unit and the kinetic energy stored in the rotating inertia [16]. The rotating mass of the generating unit is accelerated by the difference between turbine mechanical torque and generator electrical torque [17]. Thus,

$$J\dot{\omega}_m + B\omega_m = T_m - T_e \tag{3}$$

where ω_m is the angular speed of rotation in mechanical rad/sec, T_m is the mechanical torque of the turbine, and T_e is the electrical torque of the synchronous generator. The constant J is the total moment of inertia of the coupled generator and turbine rotors, and B is the damping coefficient (representing mechanical as well as electrical damping effects) [17]. The very large moment of inertia of the coupled rotors of turbine-generator set justifies the notion that $\Delta\omega$ is relatively small at least in the interval under consideration. Assuming a 2-pole round rotor generator and multiplying (3) by ω_m to express in terms of electrical power and mechanical power, yields

$$\Delta\dot{\omega} = -\frac{D}{2H}\Delta\omega + \frac{\omega_o}{2H}(P_m - P_e) \tag{4}$$

where $H = \frac{J\omega_o^2}{2S_o}$ called the "inertia constant", which is the kinetic energy of all rotating parts at synchronous speed divided by the 3-phase rated apparent power S_o. The units of H are Watt.sec/VA and also (sec.) [18]. $D = \frac{2B\omega_o^2}{S_o}$ the damping constant. P_m and P_e, is the turbine mechanical and generator electrical power, respectively in p.u. quantities, referred to the rated "nominal" apparent power of the generating unit. Also defining $\frac{d\delta}{dt} = \Delta\omega = \omega - \omega_o$ the speed deviation in rad/sec. δ is the generator load angle in electrical radians.

- *Electrical System Equations of the Generator:* The basic electrical quantities of synchronous machines (voltages, currents and flux-linkages) can be transformed from the stator three-phase reference frame into another one ($d-q$ reference frame) represented by the direct and quadrature axis of the rotor using Park's transformation [16], that is

$$\begin{aligned}
V_q &= \frac{X_d}{X_{ds}}V_s\cos\delta + \frac{X_s}{X_{ds}}E_q \\
V_d &= \frac{-X_d}{X_{ds}}V_s\sin\delta \\
V_t &= \sqrt{V_q^2 + V_d^2}
\end{aligned}$$

therefore,

$$V_t = \sqrt{\frac{X_s^2}{X_{ds}^2}E_q^2 + \frac{2X_dX_s}{X_{ds}^2}V_sE_q\cos\delta + \frac{X_d^2}{X_{ds}^2}V_s^2} \tag{6}$$

where V_t: generator terminal voltage, V_s is the receiving-end voltage of the transmission line. $X_{ds} = X_d + X_s$, X_d called the direct reactance (p.u.), $X_s = X_T + X_L$, X_T is the reactance of the transformer (p.u.), and X_L is the equivalent reactance of the transmission line (p.u.). E_q is the electro motive force (emf) in the quadrature axis. And

$$\dot{E}_q = (E_f - E_q)\frac{1}{T_d{}'} + \frac{X_d - X_d{}'}{X_{ds}{}'}V_s\Delta\omega\sin\delta \tag{7}$$

where E_f is the equivalent emf in the excitation amplifier and $T_d{}'$ is the short circuit transient-time constant in the direct axis (p.u.).

3) Excitation system: The main purpose of the excitation system is to feed the field winding of the synchronous machine with direct current so that the main flux in the rotor is generated. Further, the terminal voltage of the synchronous machine is controlled by the excitation system, which also performs a number of protection and control tasks. The excitation system model is a thyristor direct excitation system which takes the power supply from the generator terminal. In the thyristor direct excitation system, the generator field is directly controlled by the thyristor so that it responds very quickly without time delay, and described as

$$E_f = K_cU_f \tag{8}$$

where K_c is the gain of the excitation amplifier (p.u.), and U_f is the control input of the excitation amplifier. Finally the active power P_e and reactive power Q can be written as

$$P_e = \frac{V_s}{X_{ds}}E_q\sin\delta \tag{9a}$$

$$Q = \frac{V_s}{X_{ds}}E_q\cos\delta - \frac{V_s^2}{X_{ds}} \tag{9b}$$

The sampling time (T) used for on-line simulation is 10 milliseconds. A complete list of system parameters used in this work are shown in Table I. To understand the system behaviour, Fig. 2 shows the simulation of the single-machine-infinite-bus when a 5% change applied to the desired terminal voltage.

TABLE I: System Parameters

Parameter	**Value**	Unit
T_T	2.0	sec
T_G	0.2	sec
K_T	1.0	-
$\omega_\circ$	314.159	rad/sec
$f_\circ$	50.0	Hz
R	0.05	-
H	4.0	sec
D	5.0	-
X_d	1.863	p.u.
X_T	0.127	p.u.
X_L	0.485	p.u.
K_c	1.0	p.u.
T	0.01	sec

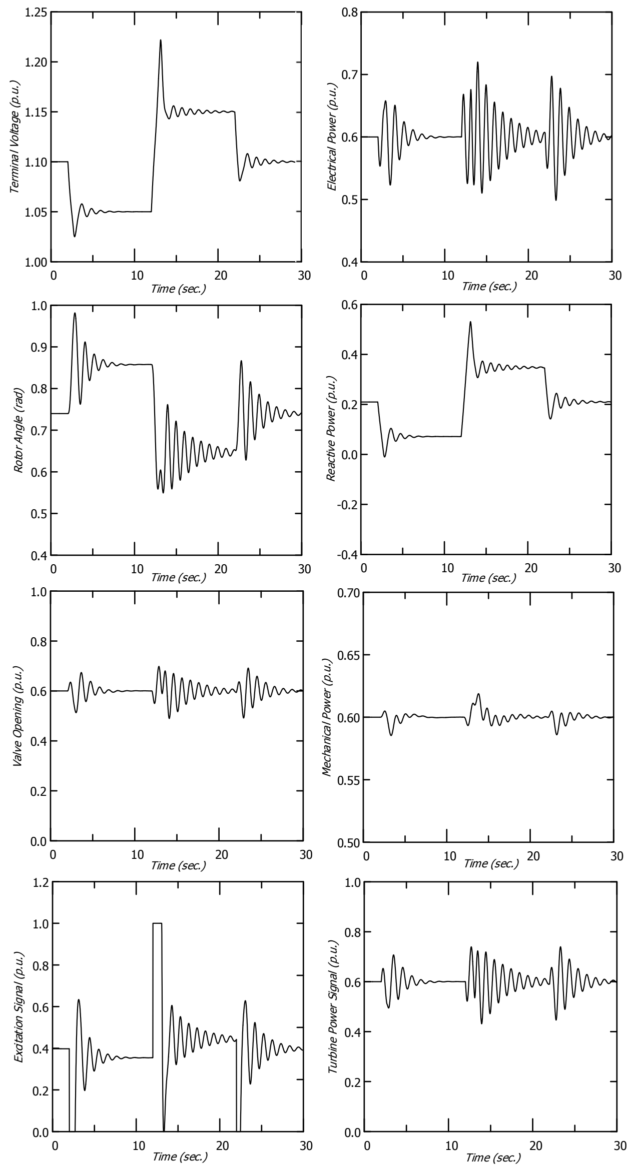


Fig. 2: Simulated system response for 5% step changes in the desired terminal voltage, (P_e=0.6 p.u.).

III. The Proposed Fuzzy Neural Identifier

A Multi-Input Multi-Output (MIMO) Fuzzy Neural Network (FuNN) is adopted to model a highly dynamic system of the turbogenerator. Figure 3 illustrates the architecture of MIMO fuzzy neural network. In this type of networks, one may specify the number of rules m and this coupled with the number of inputs n and the number of outputs O, specifies the total number of parameters. This architecture can be summarized layer by layer as follows

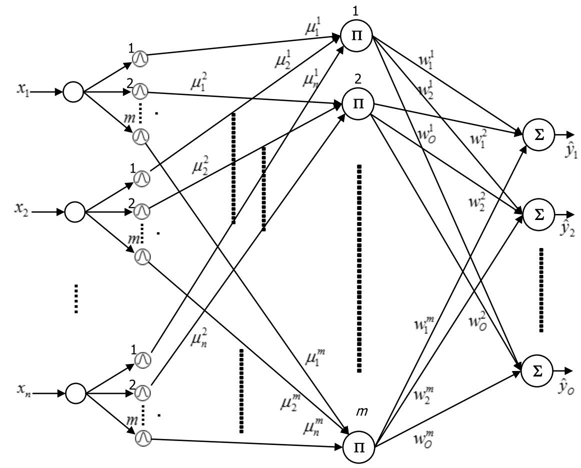


Fig. 3: Fuzzy neural network architecture MIMO (FuNN).

- *Layer I (input layer)*: Each node in this layer distributes its input variable to the nodes at layer II after they have been multiplied by the input scaling factor.
- Layer II (membership function layer): A Gaussian *membership functions* (MFs) are applied at each node in this layer. The nodes at this layer map each input x_i to every MF μ_i^j. Here the superscript j designates the jth rule of the fuzzy system:

$$\mu_i^j = exp(-\frac{1}{2}(\frac{x_i - c_i^j}{\alpha_i^j})^2) \tag{10}$$

where c_i^j and α_i^j are the center and width of the MF, respectively which belong to the ith input of the jth rule that can be updated during the learning algorithm.
- *Layer III (rule layer)*: The nodes at this layer perform algebraic product operation on the MFs that have the same jth index resulting the output of the jth node as follows:

$$u^j = \prod_{i=1}^{n} exp(-\frac{1}{2}(\frac{x_i - c_i^j}{\alpha_i^j})^2) \tag{11}$$

Where $j = 1, 2, ...m$, m is the number of rules in the fuzzy system of FuNN, and $i = 1, 2, ..., n$ where n is the number of input variables.
- *Layer IV (output layer)*: Node at this layer combines the output of each node in layer III by algebraic sum operation after being multiplied by the output weight value w^j :

$$y = \sum_{j=1}^{m} w^j u^j \tag{12}$$

A non-normalized Center of Gravity (COG) defuzzification is used here rather than normalized one. Keys behind using this modified defuzzification method are [19]: 1) The non-normalized version has a faster training rate than the normalized version. 2) A much simpler form of the input-output sensitivity equation that in a non-normalized

FuNN compared to the normalized version, and 3) Avoids the time consuming process of defuzzification. It should be noted that "j" in c_i^j is the index for the rule, while k_i in $c_i^{k_i}$ is the index for the membership function on the k_ith input universe of discourse.

The notation of $\hat{y}$ expresses the fuzzy neural network output and y is the desired output. The equation that represents the MIMO fuzzy neural network can be represented by

$$\hat{y}_z = \sum_{j=1}^{m} w_z^j u^j \tag{13}$$

where $\hat{y_z}$ is the zth network output, $z = 1, 2...O, O$ is the number of the FuNN outputs, and w_z^j is the weight for the zth output of the jth rule. There are O errors in the MIMO scheme, and the total error E can be written as follows

$$E(t) = \frac{1}{2}\sum_{z=1}^{O}(\hat{y}_z(t) - y_z(t))^2 = \frac{1}{2}\sum_{z=1}^{O}(E_z(t))^2 \tag{14}$$

The parameters of FuNN to be adjusted are as follows

$$c_i^j(t+1) = c_i^j(t) - \eta_c \frac{\partial E}{\partial c_i^j} \tag{15a}$$

$$\alpha_i^j(t+1) = \alpha_i^j(t) - \eta_\alpha \frac{\partial E}{\partial \alpha_i^j} \tag{15b}$$

$$w^j(t+1) = w^j(t) - \eta_w \frac{\partial E}{\partial w^j} \tag{15c}$$

where η_c, η_α and η_w are the learning rate of the center, width and output weight(s), respectively. It should be noted here that each output weight w_z^j depends on its corresponding zth output only, while centres c_i^j and widths α_i^j are affected by all network outputs. Taking the partial derivative of the new error equation in (14) yields

$$\frac{\partial E}{\partial c_i^j} = E_1\frac{\partial E_1}{\partial c_i^j} + E_2\frac{\partial E_2}{\partial c_i^j} + ... + E_o\frac{\partial E_o}{\partial c_i^j} \tag{16a}$$

$$\frac{\partial E}{\partial \alpha_i^j} = E_1\frac{\partial E_1}{\partial \alpha_i^j} + E_2\frac{\partial E_2}{\partial \alpha_i^j} + ... + E_o\frac{\partial E_o}{\partial \alpha_i^j} \tag{16b}$$

$$\frac{\partial E}{\partial w_i^j} = E_1\frac{\partial E_1}{\partial w_i^j} + E_2\frac{\partial E_2}{\partial w_i^j} + ... + E_o\frac{\partial E_o}{\partial w_i^j} \tag{16c}$$

thus, the new adaptation equations for c_i^j, α_i^j and w_i^j are as follows

$$\frac{\partial E}{\partial c_i^j} = (E_1 w_i^j + E_2 w_2^j + ... + E_o)\frac{(x_i - c_i^j)}{(\alpha_i^j)^2}u^j \tag{17a}$$

$$\frac{\partial E}{\partial \alpha_i^j} = (E_1 w_i^j + E_2 w_2^j + ... + E_o)\frac{(x_i - c_i^j)^2}{(\alpha_i^j)^3}u^j \tag{17b}$$

$$\frac{\partial E}{\partial w_z^j} = E_z u^j \tag{17c}$$

There are nm input membership function centres, nm input membership function widths, and m output weights. Hence, a total of $m(2n+O)$ parameters are required to describe the FuNN.

IV. Experimental Results

As mentioned earlier in section I, the forward and inverse dynamics identification are commonly used schemes to simulate highly nonlinear plants. It have been successfully applied to identify the boiler drum [20] in steam power plants. The most diffused learning technique is the error backpropagation that is an efficient application of the gradient descent method to minimize the error criteria between the model output and the desired output. Series-parallel modelling scheme [21] is globally stable and gives better convergence compared to that of the parallel modelling scheme. Therefore, the series-parallel scheme is employed in this work to develop the fuzzy neural identifier (FuNNI) because online learning is desired to identify the dynamics of the turbogenerator, and therefore avoids the feedback loop in the model which in turn allows static backpropagation to be used to adjust the FuNNI parameters. This reduces the computational overhead substantially for online training.

The inverse MIMO FuNN identification (FuNNI) block diagram is illustrated in Fig. 4. The purpose of the inverse

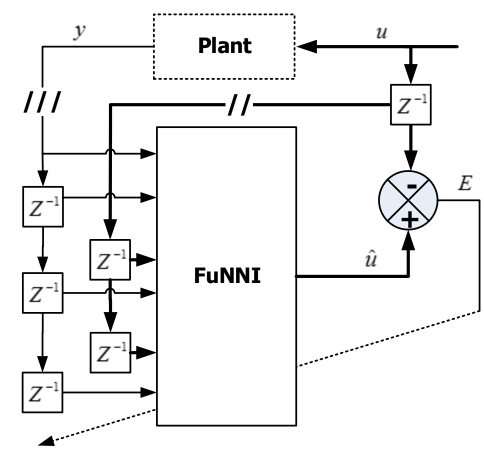


Fig. 4: MIMO FuNN inverse identification block diagram.

identifier is to build an identifier capable to model the inverse dynamics of the plant. If the inverse plant dynamics is successfully modelled, the inverse identifier can be incorporated into the control loop as a forward controller (predicts the correct action signals U_f and U_g). The control part is out of scope of this work. A single MIMO FuNNI is needed here to identify the two input variables; the exciter input U_f, and the turbine power signal U_g. The FuNNI architecture is of the form previously illustrated in Fig. 3 with sixteen inputs, twenty-five fuzzy neurons in the rules layer for each input, and two outputs. The sixteen inputs include;

- Twelve inputs are formed by the plant outputs; speed ω, terminal voltage V_t and electrical power P_e, each with their three previously delayed values and,

- Four inputs are formed by the delayed values of plant inputs (U_f and U_g) together with their two previously delayed signals. These form sixteen inputs in total to the FuNNI (see Fig. 4).

The differences between the respective inputs of the turbogenerator plant and the estimated outputs from the FuNNI form the error signals E to update parameters in the MIMO FuNNI.

The number of fuzzy partitions (fuzzy rules) are selected to be twenty-five by trial and error. Hence, there are twenty-five MFs for each input in the FuNN vary in the input universe of discourse between 0 and 1. The initial output weights are set to some random values in the range between 0 and 0.25, and the initial widths are chosen equal to 0.3. A smaller value of the initial widths may be considered with attention to be given to increase the number of pattern nodes (rules) to accommodate the necessary plant characteristics. Figure 5 shows the distribution of the initial MFs which are Gaussian functions. All simulations are curried out on a personal computer equipped with Intel Pentium IV 2.8GHz, 1GB RAM and C++ programming language. Reasonable learning rates are set (by trial and error) so that a compromise is achieved between the training time and the accuracy of the network (see Table II).

TABLE II: Parameters Setup

Parameter	Value
η_c	0.0121
η_α	0.0018
η_{w1}	0.018
η_{w2}	0.03
No. of iterations	1000
Training time	36.08 min.

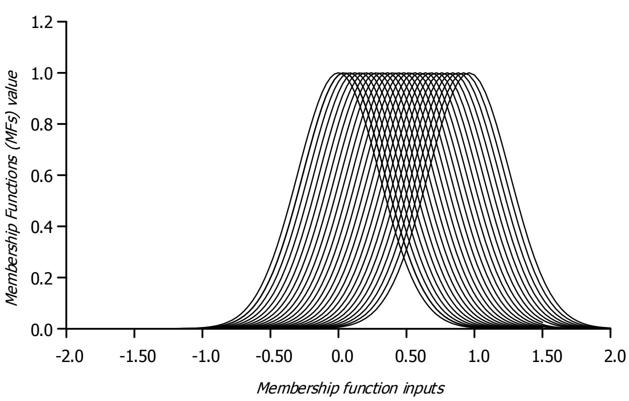
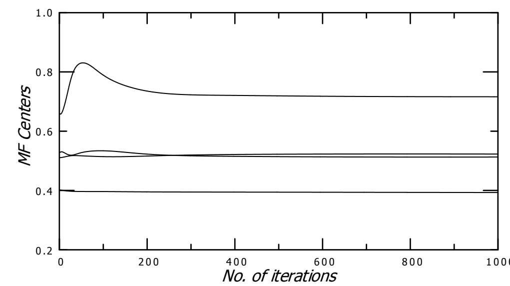
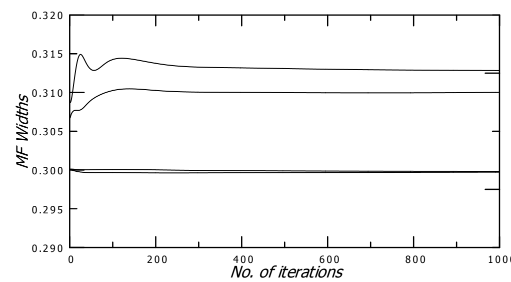


Fig. 5: Initial membership functions.

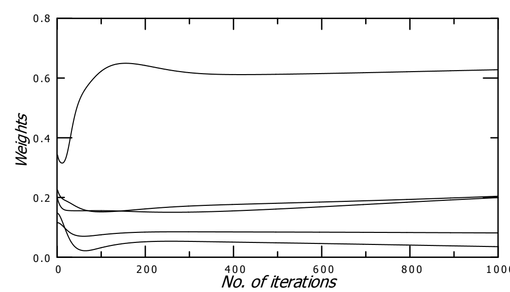
For the purpose of training the FuNNI, a few step changes are applied at the turbine power signal U_g and the excitation signal U_f (+/- a pseudo random sine wave signal with frequency equal to $k\pi T/2$, where $k = 3, 4, ...$) during a plant time interval of 120 seconds. While the number of training iterations are set to 1000, Fig. 6 shows the convergence of selected parameters of FuNNI which start to stabilize after about 500 iterations.



(a) MF centres.



(b) MF widths.

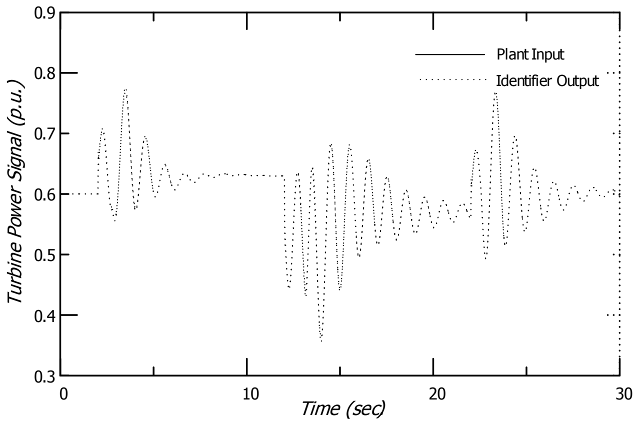


(c) Output weights.

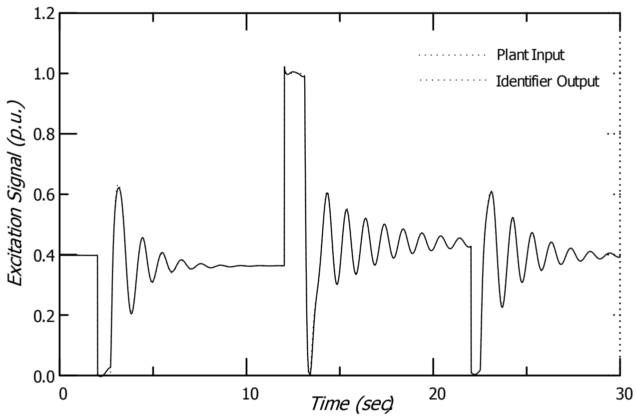
Fig. 6: Convergence of selected FuNNI parameters.

A. Step Changes in the Desired Output Power Test

After training, the FuNN identifier is tested by applying step changes in the desired output power. The two signals, namely turbine power signal U_g and excitation signal U_f, are then investigated. Figure 7 shows the system response of the actual and desired signals of U_g and U_f, respectively for simulation time duration of 30 sec and a fixed sampling time of 10 milliseconds is used in all simulations. From the figures,

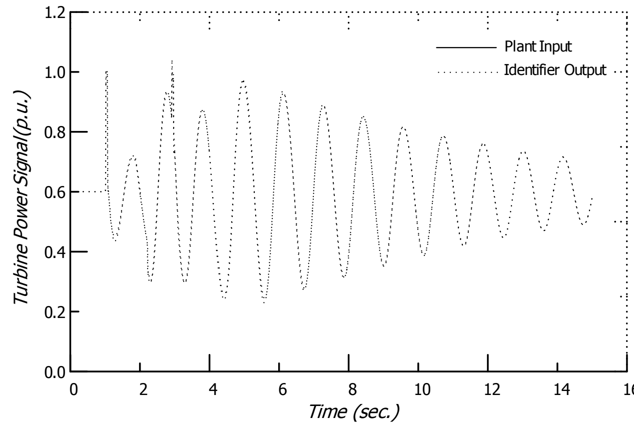


(a) Turbine power signal U_g.

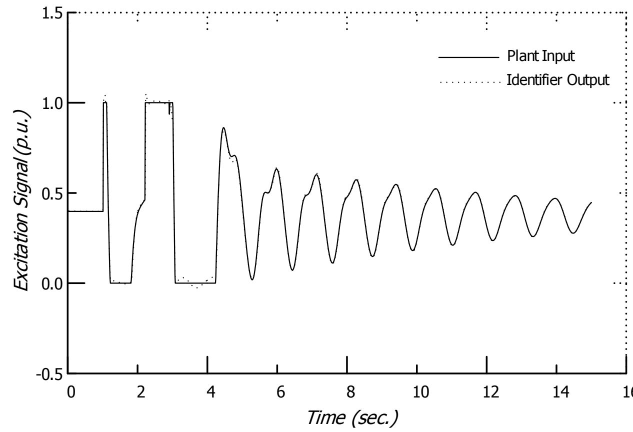


(b) Excitation signal U_f.

Fig. 7: Test under step changes in the desired output power.



(a) Turbine power signal U_g.



(b) Excitation signal U_f.

Fig. 8: Response under 3-phase short circuits.

the identifier signals effectively follow the nonlinear dynamics of the plant.

B. Three-phase Short Circuits Test

To test the robustness of the propose FuNNIs, 3-phase short circuits are applied at the infinite bus (Temporary fault + Permanent Fault). This is a more natural and severe test that typically occurs in a real power system as follows:

1) The system is in a pre-fault steady state (P_e: 0.6, V_s: 1.0, Q: 0.209, V_t: 1.1, δ (rad): 0.74, and U_f: 0.397).
2) A fault occurs at t=1 sec with fault location index[1] $\psi = 0.001$
3) The fault is removed by opening the breakers of the faulty line at t=1.05 sec (0.05 sec fault).
4) The transmission lines are restored at t=2.2 sec.
5) Another fault occurs at t=2.9 sec with fault location index $\psi = 0.001$.
6) The fault is removed by opening the breakers of the faulty line at t=2.95 (0.05 sec fault).
7) The system is in a post-fault state.

As it can be seen from Fig. 8, the FuNNI system reveals excellent tracking capability under 3-phase faults. While near accurate modelling is achieved, the maximum modelling error $E = 0.203$ is reported in the turbine power signal U_f. Whereas a less than 0.003 error is reported in the excitation signal E_f.

V. Conclusion

A MIMO fuzzy neural network scheme is applied to identify a turbogenerator in a single-machine-infinite-bus power system. A mathematical model is first developed and simulation results are generated to understand system's behaviour under various operating conditions. A feed-forward fuzzy neural network identifier (FuNNI) is adopted in a series-parallel

[1]The 3-phase fault location index is the fraction of the line to the left of the fault. This will update the infinite bus voltage V_s and the equivalent reactance of the transmission line X_L according to $V_s = V_s\psi/(1+\psi)$ and $X_L = 2\psi X_L/(1+\psi)$.

scheme which is globally stable and fast convergence compared to other conventional identification models. Empirical results have shown a good tracking capability of the FuNNIs under step changes in the terminal voltage and electrical power as well as under a severe 3-phase short circuit conditions which indicate that the proposed schemes are potentially very promising for identifying highly nonlinear multivariable turbogenerators. Furthermore, the proposed fuzzy neural identifiers are robust against the plant configuration changes during and after the occurrence of faults and is capable of continuously adapt its parameters in an online operational environment.

Although sever tests are curried out in the current simulations, it is good to quantify the reliability of the current model. Therefore, future work will involve incorporating the inverse FuNNI as an efficient forward controller to replace the conventional turbine governor and AVR to investigate the convergence. A comparison with different identification schemes such as MIMO forward FuNN identification and control would also be considered.

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