Neural Block Control for a Synchronous Electric Generator.

Victor H. Benitez*, Edgar N. Sanchez* and Alexander G. Loukianov*

*CINVESTAV, Unidad Guadalajara, Apartado Postal 31-438, Plaza la Luna, Guadalajara, Jalisco C.P. 45091, Mexico, e-mail: vbenitez@gdl.cinvestav.mx

Abstract—In this paper we present a novel identification and control scheme which is able to identify and to control a synchronous generator using a neural identifier. The generator is modelled as a full (eight) order one. A third order neural network such as the one presented in [3], is used to identify the dynamics of the synchronous generator. Moreover, a discontinuous control law based on the neural identifier is designed using the block control technique in order to track reference signals and reject external disturbances caused by generator terminal short circuits. Simulation results are presented in order to test the applicability of the proposed approach.

Keywords—Power Energy, Electro-Mechanical Systems, Nonlinear Systems, Identification, Block Control.

I. INTRODUCTION

It is known that the model of power systems is highly nonlinear; lately feedback linearization have been used [2], [8] to design continuous nonlinear controller, which overcomes the known limitations of traditional linear controllers. However the direct implementation of feedback linearization scheme results in a computationally expensive and sensitive to the plant parameters variation control algorithm. An inherent drawback of the feedback linearization approach is the non-robustness due to the need for exact knowledge, both in terms of the structure and parameters, of the power system model. Adaptive control has been used to compensate for parameter variation in a framework that allows the controller to learn the nonlinearities on-line [11].

Traditionally the control schemes of synchronous machines are commonly based on reduced order linearised model and on classical control algorithms, which ensure asymptotic stability of the equilibrium point under small disturbances, but hardly a robust controller is obtained. Due to mathematical complexity of the nonlinear state space model representing the high order single machine infinite bus system (SMIB), most papers are devoted to develop controllers based on a simplified 3rd order model. This paper presents a design which addresses the on-line identification and control trajectory tracking based on the 3rd order neural model of the power system and applying the resulting controller to the 8th order plant.

II. MATHEMATICAl MODEL

A. Full Order Mathematical Model

The complete model of the single machine infinite bus system consists of electrical and mechanical dynamics and load constraints. The electrical dynamics comprising the stator and rotor damping windings, employing the currents as the interests variables, can be modelled as

\[
L \frac{di_k}{dt} = - \begin{bmatrix} G_1 & G_2 \\ G_3 & G_4 \end{bmatrix} \begin{bmatrix} i_r \\ V_r \end{bmatrix} + \begin{bmatrix} V_s \\ L \end{bmatrix}
\]

where:

\[
L = \begin{bmatrix}
-L_d & 0 & L_m & 0 & 0 \\
0 & -L_q & 0 & L_m & 0 \\
0 & -L_d & 0 & L_m & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix},
\]

\[
G_1 = \begin{bmatrix}
-R_s & \omega L_q & 0 \\
-\omega L_d & -R_s & \omega L_m \\
0 & 0 & R_f
\end{bmatrix},
\]

\[
G_2 = \begin{bmatrix}
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix},
\]

\[
G_3 = \begin{bmatrix}
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix},
\]

\[
G_4 = \begin{bmatrix}
R_g & 0 & 0 \\
0 & R_{kd} & 0 \\
0 & 0 & R_{kg}
\end{bmatrix},
\]

with \( i_s = [i_d, i_q]^T, i_r = [i_f, i_g, i_{kd}, i_{kg}]^T, \)

\[
V_s = \begin{bmatrix} V_d \\ V_q \end{bmatrix}, V_r = \begin{bmatrix} V_f \\ 0 \\ 0 \\ 0 \end{bmatrix}^T,
\]

\( i_d \) and \( i_q \) are the direct-axis and quadrature-axis stator currents;

\( i_f \) is the field current;

\( i_{kd}, i_{kg} \) and \( i_q \) are the direct-axis and quadrature-axis damper windings currents;

\( \omega \) is the angular velocity;

\( V_d \) and \( V_q \) are the direct and quadrature-axis terminal voltages;

\( V_f \) is the excitation control input;

\( R_g \) and \( R_f \) are the stator and field resistances;

\( R_{kd}, R_{kg} \) are the damper windings resistances;
$L_d$ and $L_q$ are the direct and quadrature-axis self-inductances;
$L_f$ is the rotor self-inductance;
$L_{kd}$ and $L_{kg}$ are the direct and quadrature-axis damper windings self-inductances;
$L_{md}$ and $L_{mq}$ are the direct and quadrature-axis magnetizing inductances.

Due to the fact that flux sensitivity with respect to parameter variations is less than the currents one, it is more suitable to represent the electrical dynamics in terms of the stator current $i_s$ and the rotor fluxes \( \phi_r \), where \( \phi_r = \left[ \psi_f \quad \psi_g \quad \psi_{kd} \quad \psi_{kg} \right]^T \). Such model is obtained from (1) using the following transformation between fluxes and currents

\[
\begin{bmatrix}
i_s \\
\phi_r
\end{bmatrix} = T \begin{bmatrix}
i_s \\
i_r
\end{bmatrix}
\]

where

\[
T = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
-L_{md} & 0 & L_f & 0 & L_{md} & 0 & 0 \\
0 & -L_{mq} & 0 & L_g & 0 & L_{mq} & 0 \\
0 & -L_{mq} & 0 & L_{md} & 0 & 0 & L_{eq}
\end{bmatrix}
\]

The system (1) is transformed to the form

\[
\begin{bmatrix}
\frac{d\psi_f}{dt} \\
\frac{d\psi_g}{dt}
\end{bmatrix} = A_e (\omega) \begin{bmatrix}
i_s \\
\phi_r
\end{bmatrix} + B_e \begin{bmatrix}
V_s \\
V_r
\end{bmatrix}
\]

with $A_e (\omega) = -TL^{-1}G(\omega)T^{-1}$ and $B_e = TL^{-1}$. The complete mathematical description includes the swing equation [1]

\[
\begin{align*}
\frac{d\delta}{dt} &= -\omega - \omega_s \\
\frac{d\omega}{dt} &= \frac{\omega_s}{2H} (T_m - T_e)
\end{align*}
\]

where $\delta$ is the power angle of the generator; $\omega_s$ is the rated synchronous speed; $H$ is the inertia constant; $T_m$ is the mechanical torque applied to the shaft; and $T_e$ is the electrical torque, expressed in terms of the currents as follows

\[
T_e = (L_q - L_d) i_d i_q + L_{md} i_d (i_f + i_{kd}) - L_{mq} i_d (i_g + i_{kg})
\]

The mechanical torque $T_m$ is assumed to be a slowly varying function of time as follows

\[
T_m = 0
\]

The equilibrium equation for the external network is written as

\[
V_e = \frac{L_e}{\omega_s} \frac{di_s}{dt} + R_L (\omega) i_s + V^{\infty} Y
\]

where $R_L (\omega) = \begin{bmatrix}
R_e \\
\frac{\omega L_e}{\omega_s} \\
\omega L_e
\end{bmatrix}$ and $Y = \begin{bmatrix}
\cos \delta \\
\sin \delta
\end{bmatrix}$,

$V^{\infty}$ is the value of the infinite bus voltage; $L_e$ and $R_e$ are the transformer plus transmission line resistance and inductance. Parameter (1)-(7) are expressed in per unit.

If we select the following state variables

\[
\begin{align*}
\chi_1 &= \delta, \\
\chi_2 &= \omega, \\
\chi_3 &= \psi_f, \\
\chi_4 &= \psi_g, \\
\chi_5 &= \psi_{kd}, \\
\chi_6 &= \psi_{kg}, \\
\chi_7 &= i_d, \\
\chi_8 &= i_q.
\end{align*}
\]

Then (1)-(7) can be represented by

\[
\begin{align*}
\dot{\chi}^1 &= \chi^2 - \omega_s \\
\dot{\chi}^2 &= a_{26l} [\begin{bmatrix}
-a_{21} \chi_8 & -a_{22} \chi_7
\end{bmatrix} \chi^3 + \begin{bmatrix}
-a_{23} \chi_8 & -a_{24} \chi_7
\end{bmatrix} \chi^4 - a_{25} \chi_8 \chi_8 + T_m) \\
\dot{\chi}^3 &= A_{31} \chi^3 + A_{32} \chi^4 + A_{33} \chi^5 + B_1 v_f \\
\dot{\chi}^4 &= A_{41} \chi^3 + A_{42} \chi^4 + A_{43} \chi^5 + B_2 v_f \\
\dot{\chi}^5 &= A_{51} \chi^3 + A_{52} \chi^4 + A_{53} \chi^5 + A_{54} J \chi^3 \\
&+ A_{55} J^2 \chi^4 + A_{56} J^3 \chi^5 + A_{57} Y + B_3 v_f
\end{align*}
\]


\[
\begin{align*}
A_{31} &= \begin{bmatrix}
a_{31} & 0 & 0 & a_{41} \\
0 & a_{42} & 0 & a_{42}
\end{bmatrix}, \\
A_{32} &= \begin{bmatrix}
a_{33} & 0 & 0 & a_{41} \\
0 & a_{43} & 0 & a_{43}
\end{bmatrix}, \\
A_{33} &= \begin{bmatrix}
a_{32} & 0 & 0 & a_{42} \\
0 & a_{43} & 0 & a_{43}
\end{bmatrix}, \\
A_{34} &= \begin{bmatrix}
a_{42} & 0 & 0 & a_{43} \\
0 & a_{43} & 0 & a_{43}
\end{bmatrix}, \\
A_{44} &= \begin{bmatrix}
a_{51} & 0 & 0 & a_{51} \\
0 & a_{53} & 0 & a_{53}
\end{bmatrix}, \\
A_{45} &= \begin{bmatrix}
a_{52} & 0 & 0 & a_{52} \\
0 & a_{54} & 0 & a_{54}
\end{bmatrix}, \\
A_{46} &= \begin{bmatrix}
a_{53} & 0 & 0 & a_{53} \\
0 & a_{55} & 0 & a_{55}
\end{bmatrix}, \\
A_{47} &= \begin{bmatrix}
a_{54} & 0 & 0 & a_{54} \\
0 & a_{54} & 0 & a_{54}
\end{bmatrix}, \\
B_1 &= \begin{bmatrix}
a_{56} & 0 & 0 & a_{56}
\end{bmatrix}, \\
B_2 &= \begin{bmatrix}
a_{57} & 0 & 0 & a_{57}
\end{bmatrix}, \quad J = \begin{bmatrix}
0 & 1 & 0
\end{bmatrix}, \quad v_f \text{ is the control input to be designed.}
\end{align*}
\]

B. Reduced Mathematical Model

The machine model considered is the flux decay model (one axis model) given in [1] and [6]; exciters and governors are not included in this model. The dynamics of a single synchronous generator is described by the following equations

\[
\begin{align*}
\dot{\chi}_1 &= \chi_2 \\
\dot{\chi}_2 &= -b_1 \chi_3 \sin (\chi_1) - b_2 \chi_2 + P \\
\dot{\chi}_3 &= b_3 \cos (\chi_1) - b_4 \chi_3 + E + u
\end{align*}
\]

where $\chi_1$ is the load angle, $\chi_2$ is the shaft speed deviation from the synchronous speed, $\chi_3$ is the quadrature
axis internal voltage, $P = \frac{w_0 P_0}{E}$, $E = \frac{E_L}{T_{no}}$ and $u$ is a supplementary signal added to the field voltage, as a control input. The coefficients $b_i, i = 1, ..., 4$ are positive [4].

III. RECURRENT NEURAL NETWORKS

The nonlinear identification scheme used is based on the Recurrent High Order Neural Networks (RHO") presented in [5] and the modified version proposed by reference [10]. This neural identifier allows to use both on-line adjustable parameter and fixed ones. The state of each neuron is represented by

$$
\dot{x}_i = -a_i x_i + \sum_{k=1}^{L_i} w_{ik} z_{ik} + \sum_{j=L_i+1}^{L_i'} w_{ij} z_{ij}
$$

(10)

where: $a_i > 0$, $x_i$ is the neuron state, $w_{ik}$ are the on-line updated weights, $z_{ik}$ are multiplication of sigmoid functions for $x$ or $u$, $w_{ij}$ are fixed weights, which allows to incorporate to the identification model a priori information about the plant structure, $z_{ij}$ are either functions of $x$ or $u$, $L_i$ is the number of weights to be updated, $L_i'$ is the number of fixed weights and

$$
z_{ik}(x, u) = \begin{bmatrix} z_{i1} \\ z_{i2} \\ \vdots \\ z_{iL_i} \end{bmatrix} = \begin{bmatrix} \Pi_j \eta_{j1} y_j^{(1)}(x) \\ \Pi_j \eta_{j2} y_j^{(2)}(x) \\ \vdots \\ \Pi_j \eta_{jL_j} y_j^{(L_j)}(x) \end{bmatrix}
$$

(11)

with

$$
y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \\ y_{n+1} \\ \vdots \\ y_{n+m} \end{bmatrix} = \begin{bmatrix} s(x_1) \\ \vdots \\ s(x_n) \\ s(t_1) \\ \vdots \\ s(t_m) \end{bmatrix}, \quad s(x) = \frac{\alpha}{1 + e^{-\beta x}} + \varepsilon,
$$

$s(x)$ is the well-known sigmoid function if $\alpha = \beta = 1$ and $\varepsilon = 0$. To simplify the RHONN model, we can represent (10) as

$$
\dot{x}_i = -a_i x_i + w_i^T z_i + w_i^T z_i
$$

(12)

where

\begin{align*}
   w_i &= \begin{bmatrix} w_{i,1} & \cdots & w_{i,L_i} \end{bmatrix}^T \\
   w_i' &= \begin{bmatrix} w_{i,(L_i+1)} & \cdots & w_{i,L_i'} \end{bmatrix}^T \\
   z_i &= \begin{bmatrix} z_{i,1} \\ \vdots \\ z_{i,L_i} \end{bmatrix}^T \\
   z_i' &= \begin{bmatrix} z_{i,(L_i+1)} \\ \vdots \\ z_{i,L_i'} \end{bmatrix}^T
\end{align*}

Finally we can reduce (12) to

$$
\dot{x}_i = -a_i x_i + w_i^T z_i
$$

(13)

with

$$
w_i = \begin{bmatrix} w_i' & w_i'' \end{bmatrix}^T, \\
z_i = \begin{bmatrix} z_i' & z_i'' \end{bmatrix}^T
$$

A. Neural Model for Synchronous Generators

This section closely follows [3], where a recurrent high order neural network identification and control scheme is proposed based on model (9), which allows to achieve transient stability for synchronous generators. This neural identifier as well as the on-line weight adaptive law used by [3, and references within] are reproduced here for the sake of completeness. The neural model proposed for the synchronous generator third order model is

$$
\begin{align*}
  \dot{x}_1 &= -a_1 x_1 + \xi_1 \\
  \dot{x}_2 &= -a_2 x_2 + w_2 S(x_2) + w_2 S(x_1) S(x_3) + \xi_2 \\
  \dot{x}_3 &= -a_3 x_3 + w_3 S(x_1) + w_3 S(x_3) + \xi_3
\end{align*}
$$

(14)

In accordance with (13), the structure of (14) consists of parameters to be adjusted such as $w_2 = \begin{bmatrix} w_{21} & w_{22} \end{bmatrix}^T$ and $w_3 = \begin{bmatrix} w_{31} & w_{32} \end{bmatrix}^T$; the fixed terms $\xi_i$ which includes the fixed parameters, given by $\xi_1 = a_1 x_1 + x_2$, $\xi_2 = P$ and $\xi_3 = E + u$. It is worth to point out that we modified the $\xi_1$ term in (14) to includes the rated synchronous speed $\omega_s$ of (8) as a fixed parameter. As a result, the $\xi_1$ term is modified as follows

$$
\xi_1 = a_1 x_1 + x_2 - \omega_s
$$

(15)

This modifications allows to apply (14) to the full order nonlinear model of the synchronous generator (8).

B. Updating Weight Law

The adaptive law is defined as

$$
\dot{w}_i = -\varepsilon_i \Gamma_i^{-1} z_i
$$

(16)

where $\Gamma_i$ is a symmetric positive definite matrix and $\varepsilon_i = x_i - \chi_i$ is the $i$-th identification error. Using (16) as the updating weight law ensures the boundedness of the weights and guarantees that the identification error converges to zero as is demonstrated in [3].

C. Robust Learning Algorithm

The learning algorithm (16) considers no modeling error, i.e., it was assumed that there exist weight vectors $w_i^*$, such that each state of the unknown dynamical system

$$
\dot{\chi} = f(\chi)
$$

(17)

satisfies

$$
\dot{\chi}_s = -a_i x_i + w_i^T z(\chi, u)
$$

(18)

In many cases this assumption is violated. This is mainly due to an insufficient number of higher-order
terms in the RHONN model. The standard weight adjustment law (16) is modified by the addition of the leakage term \( \sigma_i \Gamma_i^{-1} w_i \), whose objective is to prevent the weight values from drifting to infinity [9]. The modification is done as follows

\[
\dot{w}_i = -\Gamma_i^{-1} (e_i z_i - \sigma_i w_i)
\]

where \( \sigma_i \) is determined as

\[
\sigma_i = \begin{cases} 
0 & \text{if } ||w_i|| \leq M_i \\
\left( \frac{||w_i||}{M_i} \right)^q & \text{if } M_i < ||w_i|| \leq 2M_i \\
\sigma_{i0} & \text{if } ||w_i|| > 2M_i 
\end{cases}
\]

with the constants \( q \geq 1 \) and \( \sigma_{i0}, M_i > 0 \). For further detail see reference [9], which discuss the respective proof.

IV. CONTROL ALGORITHM

The objectives are to control the angle \( \delta \) and the speed \( \omega \) such that both signals are able to track a desired reference signals and reject external disturbances. Employing the block control technique [7] and using \( \delta_r = 1.3314 \), let define the error signal as

\[
z_1 = x_1 - \delta_r
\]

The dynamics for (20) can be obtained from (14) and (15) as

\[
\dot{z}_1 = x_2 - \omega_s
\]

Using \( x_2 = -k_1 x_1 + z_2 + \omega_s \), (21) is modified as

\[
\dot{z}_1 = -k_1 z_1 + z_2
\]

with \( \dot{z}_2 \) given by

\[
\dot{z}_2 = -a_2 x_2 + w_2 s(x_1) s(z_2) + w_2 s(x_1) s(z_3) + k_2 (x_2 - \omega_s) + P
\]

In the next step, for (23) we introduce the following switching surface \( z_3 \)

\[
\dot{z}_3 = -k_3 z_2 + z_3
\]

where \( k_1, k_2 > 0 \). The switching function \( z_3 \) is derived using (23) and (24) as follows

\[
z_3 = -a_2 x_2 + w_1 s(x_1) s(z_3) + k_1 (x_2 - \omega_s) + P + k_2 z_2
\]

It is clear that if we select the sliding manifold as

\[
z_3 = 0
\]

then the motion on this manifold will be described by the linear system defined by (22) and (24) with the desired dynamics. To guarantee the sliding mode in the manifold (26), the motion projection on subspace \( z_1, z_2 \) is derived as [12]

\[
\dot{z}_3 = \eta + w_2 s(x_1) s'(x_3) u
\]

where \( \eta = \frac{\partial \dot{x}}{\partial x_1} + \frac{\partial \dot{x}}{\partial x_2} + \frac{\partial \dot{x}}{\partial \dot{x}} \), \( s'(x) = \frac{\partial s(x)}{\partial x} \), with \( r = \begin{bmatrix} \delta_r & \omega_s \end{bmatrix}^T \). Then taking into account the following bound

\[
|u| \leq U_0, \ U_0 > 0
\]

the discontinuous control law is defined as

\[
u = -U_0 \text{sign}(w_2 s(x_1) s'(x_3)) \text{sign}(z_3)
\]

The stability condition of the origin \( z_3 = 0 \) for the closed-loop system (27), (28) is given as

\[
\dot{z}_3 = \eta - U_0 |w_2 s(x_1) s'(x_3)| \text{sign}(z_3)
\]

if the following inequalities are satisfied

\[
|\eta| < U_0 |w_2 s(x_1) s'(x_3)|
\]

a sliding mode motion occurs on the manifold (26) in a finite time, then the tracking error \( z_1 \) will tend asymptotically to zero (in accordance with (22)). This motion is invariant with respect to generator parameters variations and external disturbances.

V. SIMULATIONS

The performance of the proposed identification and control scheme (Fig.1) was applied on the complete 8th order model (8) of the generator connected to an infinite bus through a transmission line (Fig.2).

The parameters of the model (8) are given as
which are in p.u except when indicated. The parameters for the neural identifier are \( a_2 = 1, a_3 = 2, \)
\( \alpha_2 = \alpha_3 = 2, \beta_2 = 20, \beta_3 = 20, \zeta = 0.01, \Gamma_1^{-1} = 800, \Gamma_3^{-1} = 0.2. \) The identification and control stages are indicated as follows:

**Stage 1:** The open loop system is identified on-line by the neural network at time \( t = t_1; \)

**Stage 2:** Identification error is very close to zero and the control law is applied in \( t > t_1; \) the states \( \chi_1, \chi_2 \) tracks the desired references signals at \( t = t_r; \)

**Stage 3:** A fault occurs at \( t = t_{f1}; \)

**Stage 4:** The fault is removed by opening the breakers of the faulty line at \( t = t_{f2}; \)

**Stage 5:** The system is in a postfault state.

The identification and control sequence for \( \delta \) is showed in Fig.3. The short circuit fault occurs at \( t_{f1} = 40 \) sec and cleared at \( t_{f2} = 40.15 \) sec. The difference \( t_{f2} - t_{f1} \) is called the critical clearing time, Fig.4 shows the performance of the identification and control scheme for \( \omega. \)

The weights remains bounded during the complete sequence at all stages (Fig.5). The Fig.6 shows the discontinuous control law performance.
VI. CONCLUSIONS

An identification and control scheme is proposed based on a reduced order neural network which is able to identify a full order dynamics for synchronous generators. The sliding mode control law forces the closed loop trajectory to converge and to stay in the sliding manifold, which guarantees that the tracking error is zero. Moreover, simulations shows that the scheme proposed preserves stability and good performance when a short circuit fault is included.

This paper constitutes a first attempt to use recurrent neural networks in order to build reduced order models for synchronous generator; and to develop control laws, based on this reduced model, which are able to handle the full order dynamics.

Acknowledgments — The authors thank the support of CONACYT, Mexico, on Projects 39866Y and 3960A.

REFERENCES