Chaotic Oscillation of a Three-bus Power System Model Using Elman Neural Network

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Abstract

Chaotic oscillation of power systems was deeply studied in this paper. By using a three-bus power system, route may cause chaotic behavior in power systems are evaluated, illustrated and discussed. Chaotic oscillation of power systems was modeled using Elman neural network because the Elman neural network has a simple form. Backpropagation algorithm with adaptive learning rate and momentum was proposed in this research. Performance of learning rate with momentum was better than learning rate without momentum. Chaotic behaviors in a power systems appeared due to the system operated in critical mode. A Chaotic behavior in power systems was detected by appearing a strange attractor (a chaotic attractor) in phase-plane trajectory.

Keywords: power systems, Elman neural network, chaotic attractor, phase-plane trajectory

1. Introduction

In recent years, electric power consuming has grown up rapidly. On the other hand, the power plants and transmission systems being built are very slow due to environmental and economical constraints. This condition will make the power systems operate in critical mode at the boundary of stability region. Meanwhile, chaotic phenomena is one type of un-deterministic oscillations exist in deterministic systems such as in power system model. Chiang et al, have built voltage collapse model, both physical explanations and computational considerations of this model are presented. Static and dynamic models are used to explain the type of voltage collapse, where the static is used before a saddle-node bifurcation and the dynamic model is employed after the bifurcation [1]. Lyapunov exponent, measuring how rapidly two nearby trajectories separate from one another within state space and broad-band spectrum was used to confirm the observation [2]. Within the range of loading conditions, the sensitive dependence feature of chaotic behaviors makes the power system unpredictable after a finite time. In addition, within the range the effectiveness any control scheme was questionable and should be evaluated based on state vector information. Furthermore, nonlinear phenomena including bifurcation, chaos and voltage collapse occurred in a power system model. The present of the various nonlinear phenomena was found to be a crucial factor in the inception of voltage collapse in this...
model. The problem of controlled and suppressed of the presence of non-linear phenomena in power systems were addressed here in this paper. The bifurcation control approach is approach to modify the bifurcations and to suppress chaos [3,4]. The presence of chaos in a power system causing seriously unstable problem was studied by Yu, et al.[5]. The existence chaos in power systems due to disturbing of energy at rotor speed has been found in Ref.[6]. One scheme of chaos utility was used on electrical systems for smelting which was based on chaos control. Lei et al. Demonstrated that chaotic steel-smelting ovens regulate their heating current according to chaos control theory [7]. A control system using a neural network controller was presumed to be able to stabilize the unstable focus points of 2-dimensional chaotic systems; although, Konishiand Kokame stated that the control system did not require this presumption [8]. Elman neural network was used to predict short-term load forecasting in power systems [9]. Modeling of chaotic behavior using RNN has been studied in [10]. Various studies on controlling transient chaos have been carried out, such as those by Dhamala et al., and Dhamala and Lai attempted to control transient chaos in power systems using a data time series [11,12]. Strategies for controlling chaos in process plants have been tested on the Henon map discrete chaotic system [13].

In this paper, we focused on the cause of chaotic oscillation in power systems and its model. By using Elman neural network model is proposed. The reason of using the Elman neural network because the Elman network is able to train data both on present input and on past output, and other reason because an Elman RNN has simple form.

This paper is organized as follows: in advance, power system model used in this research is given in Section 2. Then, Elman neural network model is explained in Section 3. Chaotic behavior due to sensitivity of initial condition and analysis a chaotic behavior are presented in Section 4 and 5, respectively. The conclusion is given in the last section.

2. Power System Model

A Synchronous machine was modeled as a voltage \( E_{q0} \) behind a direct reactance \( x_d \). The voltage magnitude was assumed as remaining constant at the pre-disturbance value, as shown in Fig.1(a). De Mello and Concordia as well as Padiyar and Kundur derived of a machine connected to an infinite bus [13,14]. Meanwhile, if saturation and the stator resistance were neglected, the system condition was balanced with a static load. The mechanical mode block diagram of single-machine connected to infinite bus is shown in Fig.1(b).
The machine was connected to infinite bus and supplied the load. Then the armature current flowed from the machine to the load. This current caused electrical torque on the stator winding, and vice versa. The mechanical torque was produced by flux through the rotor winding. Meanwhile, when the rotor speed was constant, the rotor speed followed the synchronous speed. When there was imbalance energy, the rotor speed accelerated or decelerated and caused the swing equation. The swing equation is represented as follows:

\[ H\ddot{\delta} + D \Delta \omega = T_e = T_m - T_e \]  

Where \( D \), \( \Delta \omega \) are amping constant and rotor speed deviation, respectively. Eq.1 is a basic equation for mechanical mode of single machine connected to infinite bus. Furthermore, the Eq. 1 can be expressed as follows:

\[ \dot{\delta} = \omega_n \Delta \omega \]  (2)

\[ \Delta \dot{\omega} = \frac{1}{M} (\Delta T_m - \Delta T_e - D \Delta \omega) \]  (3)

Where \( \Delta T_m \), \( \Delta T_e \), \( \delta \), \( \Delta \omega \), \( D \) and \( M \) are mechanical torque, electrical torque, power angle, speed rotor, damping constant, inertia constant respectively. The system was developed from Ref.[3] and shown in Fig.3, which is regarded as one synchronous machine supplying power to a local dynamic load shunt with a capacitor (Bus 2) and connected by weak tie line to the external system (Bus 3). The system equations are:

\[ \dot{\delta} = \Delta \omega \]  (4)

\[ \Delta \dot{\omega} = 16.667 \sin (\delta - \delta + 0.087)V_L - 3.333 d \Delta \omega + 1.881 \]  (5)

\[ \dot{\delta}_L = 496.872V_L^2 - 166.667 \cos (\delta - 0.087)V_L - 93.333V_L \]  (6)

\[ V_L = -78.764V_L^2 + 26.217 \cos (\delta - 0.012)V_L + 14.523V_L + 104.869 \cos (\delta - 0.135) - 5.229Q_{id} - 7.033 \]  (7)

Table 1. Power system parameters

<table>
<thead>
<tr>
<th>( Y_0 )</th>
<th>( Y_m )</th>
<th>( \theta_0 )</th>
<th>( \theta_m )</th>
<th>( V_0 )</th>
<th>( V_m )</th>
<th>( P_m )</th>
<th>( M )</th>
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<td>20</td>
<td>5.0</td>
<td>-5</td>
<td>-5</td>
<td>1.0</td>
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<td>0.3</td>
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<tr>
<td>D</td>
<td>T</td>
<td>C</td>
<td>( K_{pe} )</td>
<td>( K_{pv} )</td>
<td>( K_{qpe} )</td>
<td>( K_{qv} )</td>
<td>( K_{qv2} )</td>
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<td>0.0</td>
<td>8.5</td>
<td>12</td>
<td>0.4</td>
<td>0.3</td>
<td>-0.0</td>
<td>-2</td>
<td>2.1</td>
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<td>0</td>
<td>3</td>
<td>8</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>
Figure 2. One line diagram power system with 3 buses.

\[ \delta, \Delta \omega, d, Q_L, \delta_L, V_L, \] are the power angle, rotor speed deviation, damping constant, reactive load, voltage angle and magnitude at load bus, respectively. Eqs.4,5,6, and 7 can be simplified into a uniform equation in Eq.8.

\[
\dot{x} = f(x, \lambda), \quad x \in R^n, \lambda \in R^p, \quad \text{Eq.8}
\]

Where \( x \) is vector state variables and \( \lambda \) is vector of parameters. The state variables are \( x = [\delta, \Delta \omega, \delta_L, V_L]^T \). Superscript \( T \) denote transpose of the associate vector.

3. Elman Neural Network Model

Recurrent Elman network commonly is a two-layer network with feedback from the first-layer output to the first-layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. A two-layer Elman network is shown in Fig.3. The Elman network has tansig neurons in its hidden (recurrent) layer and purelin in its output layer. The Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Thus, even if two Elman networks with the same weight and bias, are given identical inputs at a given time step, their outputs can be different due to different feedback states. Because network can store information for future reference, it is able to learn temporal pattern as well as spatial patterns \[15,16,17,18] \). The Elman network can be trained to respond and to generate, both kinds of patterns.

\[
\begin{align*}
a_1(n) &= \text{tansig}[W_{i1}^1 p + LW_{i1}^1 a_1(n-1) + b_1] \\
a_2(n) &= \text{purelin}[LW_{i2}^1 a_1(n) + b_2] \quad \text{Eq.9}
\end{align*}
\]

The architecture 4:8:8:4 RNN is used in this research. Where \( p, a_1(n), a_2(n), LW_{i1}, LW_{i1}, LW_{i2}, b_1, b_2 \) are the vector input, recurrent-layer output, purelin-layer output, weight first-layer, weight hidden layer back to first-layer, weight hidden layer to output layer and biases, respectively.

Figure 3. Elman recurrent neural network block diagram[18]
The RNN was trained by using 1000 data points. Tansig and purelin activation function were used at hidden layer and at output layer, respectively. Data time series were obtained from the mathematical (exact) model in Eqs. 4-7, respectively. The network performance is measured by mean square error (MSE). Formula of the MSE can be expressed by equation as follow:

\[ \text{MSE} = \frac{1}{k} \left[ \sum_{n=1}^{k} (\hat{x}_n - x_n)^2 \right] \]  \hspace{1cm} (10)

Where \( k \), \( x_n \), and \( \hat{x}_n \) are the size of data, input and estimation \( n^{th} \) data.

4. Chaotic Behavior due to Sensitivity of Initial Condition

Chaos definition and its properties have been given by Devaney and Alligood et al.[19,20]. Sensitivity of initial condition is one type of chaos properties. It is described by existing route to chaotic behavior in power systems caused by sensitivity of initial condition rotor speed (\( \omega_0 \)). Initial rotor speed (\( \omega_0 \)) in power systems was presented by disturbing of energy (DE). Kinetic energy disturbance was related to rotor speed deviation only. The large rotor speed deviation was implemented as a large DE. When DE was smaller than the value of 1.3824 rad/s (\( \omega_0 < 1.3824 \) rad/s), a power system converged to a stable equilibrium point. When the DE was increased, the convergence became more difficult. At \( \omega_0 = 1.3825 \) rad/s, power systems produced route to a chaotic behavior in a longer time. When the DE was from 1.3825 to 17003 rad/s, the final states were controlled by a chaotic behavior. Furthermore, while the DE excess than 1.7004 rad/s, the system went to divergence or voltage collapse. Based on the simulation result it is shown that chaotic behavior in power systems due to disturbing of energy at the rotor speed deviation.

<table>
<thead>
<tr>
<th>( \omega_0 ) (rad/s)</th>
<th>Times (s)</th>
<th>Final state</th>
<th>Time response</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>1000</td>
<td>Equilibrium point</td>
<td>Fig.4(a)</td>
</tr>
<tr>
<td>1.3824</td>
<td>1000</td>
<td>Equilibrium point</td>
<td>Fig.4(b)</td>
</tr>
<tr>
<td>1.3825</td>
<td>1000</td>
<td>Chaotic</td>
<td>Fig.5(a)</td>
</tr>
<tr>
<td>1.7003</td>
<td>1000</td>
<td>Chaotic</td>
<td>Fig.5(b)</td>
</tr>
<tr>
<td>1.7004</td>
<td>10</td>
<td>Divergence</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 4. Simulation results with equilibrium point state
5. Result and Analysis

In this research, RNN initial simulation parameters were taken: learning rate train parameter = 0.17; increment learning rate = 1.2; decrement learning rate = 0.6; and momentum learning rate = 0.75. The training performance of RNN using adaptive learning rate and adaptive learning rate with momentum are listed in Table 3. The training process is organized as follows: performances (MSE) are obtained to $14.7001 \times 10^{-4}$ and $4.2209 \times 10^{-4}$ at disturbance $\omega_0 = 0.5$ rad/s for algorithm backpropagation adaptive learning rate (trainda) and backpropagation learning rate algorithm with momentum (traindx), respectively. Moreover, performances were obtained to $16.8361 \times 10^{-4}$ and $4.6115 \times 10^{-4}$ at disturbance $\omega_0 = 1.3825$ rad/s. Furthermore, performances were obtained to $17.4185 \times 10^{-4}$ and $4.9442 \times 10^{-4}$ at the disturbance $\omega_0$ at the value of 1.7003 rad/s. During the training process the best performance was obtained to $4.2209 \times 10^{-4}$ at the disturbance of 0.5 rad/s.

![Figure 5. Simulation results with chaotic state](image1)

![Figure 6. (a). Chaotic behavior of the rotor speed deviation](image2)

(b). Magnified of Fig. 5 from time = 0 to time = 50 s
Figs. 7-9 show the time responses of an exact and Elman recurrent neural network (RNN) model. Fig. 7(a) shows rotor speed deviation ($\Delta\omega$) time response which was oscillated due to the disturbance occurred at $\omega_0 = 1.7003$ rad/s. Rotor speed oscillations exist in range from $1.6052$ to $1.5679$ rad/s and from $-1.511$ to $1.6045$ for the exact and RNN, respectively. Fig. 7(b) shows error signal of the rotor speed deviation; where the error signal is the difference of the exact and RNN model of the rotor speed deviation.

Voltage angle ($\delta$) at Bus 2 is affected by disturbing of energy (DE) at generator bus ($\omega_0 = 0.5$ rad/s). The oscillation on voltage angle occurred at generator bus in a few second, then this oscillation decreased gradually and route to equilibrium point (fixed point) at point of $0.1128$ and $0.1116$ rad for exact and RNN models, respectively. The error signal of the voltage angle was measured by mean square error (MSE = 3.8193%), and these results are shown in Table 4.
Figure 9. The voltage magnitude ($V_L$) time response at $\omega_0 = 1.7003$ rad/s (a). Blue = exact model; red = RNN model (b). Error signal of the $V_L$.

The voltage angle oscillation increased at the disturbance 1.3825, 1.600 and 1.7003 rad/s for exact model with amplitude in ranges (0.0600 to 0.1995 rad), (0.0351 to 0.2730 rad), (0.0345 to 0.2748 rad) and (0.0340 to 0.2756 rad), respectively. And the oscillation for RNN model are from 0.0501 to 0.1879 rad, from 0.0460 to 0.2644 rad, from 0.0332 to 0.2618 rad and from 0.0342 to 0.2613 rad, respectively. This oscillation occurred in a longer time. Voltage angle time response occurring at disturbance $\omega_0$1.7003 rad/s can be shown in Fig. 8.

When the disturbance ($\omega_0$) at the value of 0.5 rad/s, the voltage magnitude oscillated in a few seconds. Furthermore, its decreased gradually route to equilibrium state (fixed point) at point 1.095 pu and 1.08 for exact and RNN model, respectively. By increasing disturbance at $\omega_0$ 1.3824 rad/s voltage magnitude is oscillated in a longer time in ranges (0.9967 to 1.1207 pu) and then amplitude reduced and fixed point at 1.1095 pu (1520 s).

On the opposite, when the disturbing of energy was increased up to 1.3825, 1.600 and 1.7003 rad/s, voltage magnitude oscillated for the exact model where the amplitude increased from 0.8307 to 1.1220 pu, from 0.8285 to 1.1118 pu, and from 0.8290 to 1.1119 pu, respectively. And the oscillation for RNN model was in the ranges from 0.8497 to 1.1158 pu, from 0.8580 to 1.1235 pu and from 0.8642 to 1.1185 pu, respectively. In Fig. 9, we can show that the voltage magnitude of the exact and RNN models exhibit chaotic behavior.

### Table 3. Performance of training algorithm using learning rate momentum

<table>
<thead>
<tr>
<th>$\omega_0$ (rad/s)</th>
<th>Training Times ($\times 10^2$)</th>
<th>Performances MSE ($\times 10^4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>traingda</td>
<td>traingdx</td>
</tr>
<tr>
<td>0.5</td>
<td>69.3861</td>
<td>37.403</td>
</tr>
<tr>
<td>1.3824</td>
<td>68.3250</td>
<td>42.342</td>
</tr>
<tr>
<td>1.3825</td>
<td>67.3329</td>
<td>36.750</td>
</tr>
<tr>
<td>1.7003</td>
<td>70.5781</td>
<td>41.840</td>
</tr>
</tbody>
</table>

State trajectory (orbit) of the $\Delta\omega$ against $\Delta\delta$s shown in Fig.10, where many circles are made by themselves with boundary ranges from -1.6011 to +1.5535 rad/s and from -0.1165 to +0.7583 rad for the $\Delta\omega_{min}, \Delta\omega_{max}$ and $\Delta\delta_{min}, \Delta\delta_{max}$, respectively. The state trajectories of the RNN model are made in ranges from -1.6020 to +1.5524 rad/s and from -0.1145 to +0.7598 rad, respectively. The attractive form of the $\Delta\omega$ or $\Delta\delta$s known as strange attractor (chaotic attractor). The strange attractors of the $\Delta\delta$s against $V_L$ are shown in Fig. 11. The strange attractor coordinates were from 0.0345 to 0.2748 rad and from 0.8285 to 1.1118 pu for $\delta_{L_{max}}$, $\delta_{L_{min}}$ and $V_{L_{max}}, V_{L_{min}}$, respectively.
Meanwhile, the RNN model of the $\delta-V_L$ was from 0.0332 to 0.2618 rad and from 0.8280 to 1.1235 pu for $\delta_{\text{max}}-\delta_{\text{min}}$ and $V_{\text{Lmax}}-V_{\text{Lmin}}$, respectively.

Table 4: Power system state when variation of the DE was applied.

<table>
<thead>
<tr>
<th>$\omega_0$ &amp; Model</th>
<th>$\delta$ (rad)</th>
<th>$\omega$ (rad/s)</th>
<th>$\delta_c$ (rad/s)</th>
<th>$V_L$ (pu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5 Exact</td>
<td>eq 0.3095</td>
<td>osc 0.2104 to</td>
<td>eq</td>
<td>eq 1.095</td>
</tr>
<tr>
<td>RNN</td>
<td>eq 0.3194</td>
<td>osc 0.2008 to</td>
<td>eq</td>
<td>eq 1.008</td>
</tr>
<tr>
<td>MSE (%)</td>
<td>0.2636</td>
<td>11.1792</td>
<td>3.8193</td>
<td>8.7051</td>
</tr>
<tr>
<td>1.3824 Exact</td>
<td>osc 0.0245</td>
<td>osc 1.1546 to</td>
<td>osc 1.0600 to</td>
<td>osc 1.9967 to</td>
</tr>
<tr>
<td>RNN</td>
<td>osc 0.0256</td>
<td>osc 1.0246 to</td>
<td>osc 1.0501 to</td>
<td>osc 1.9970 to</td>
</tr>
<tr>
<td>MSE (%)</td>
<td>3.9625</td>
<td>6.3023</td>
<td>0.2040</td>
<td>0.1154</td>
</tr>
<tr>
<td>1.3425 Exact</td>
<td>osc 0.1156</td>
<td>osc 1.5711 to</td>
<td>osc 1.0351 to</td>
<td>osc 1.8307 to</td>
</tr>
<tr>
<td>RNN</td>
<td>osc 0.1148</td>
<td>osc 1.5734 to</td>
<td>osc 1.0460 to</td>
<td>osc 1.8497 to</td>
</tr>
<tr>
<td>MSE (%)</td>
<td>0.68</td>
<td>0.23</td>
<td>1.09</td>
<td>1.10</td>
</tr>
<tr>
<td>1.6000 Exact</td>
<td>osc 0.1165</td>
<td>osc 1.6011 to</td>
<td>osc 0.0345</td>
<td>osc 0.8285 to</td>
</tr>
<tr>
<td>RNN</td>
<td>osc 0.1645</td>
<td>osc 1.6020 to</td>
<td>osc 0.0332 to</td>
<td>osc 0.8580 to</td>
</tr>
<tr>
<td>MSE (%)</td>
<td>2.163</td>
<td>2.8779</td>
<td>0.0460</td>
<td>0.0407</td>
</tr>
<tr>
<td>1.7003 Exact</td>
<td>osc 0.1157</td>
<td>osc 1.6052 to</td>
<td>osc 0.0340</td>
<td>osc 0.8290 to</td>
</tr>
<tr>
<td>RNN</td>
<td>osc 0.1345</td>
<td>osc 1.5111 to</td>
<td>osc 0.0342 to</td>
<td>osc 0.8642 to</td>
</tr>
<tr>
<td>MSE (%)</td>
<td>1.522</td>
<td>17.8296</td>
<td>0.1284</td>
<td>0.1470</td>
</tr>
</tbody>
</table>

Note: eq = equilibrium point (fixed point); osc = oscillation.

Figure 10. State trajectory of the $\Delta\omega-\delta$ when disturbance was applied at $\omega_0 = 1.600$ rad/s.
Furthermore, existence of the chaotic attractors can also be depicted in Figs. 12 and 13 for the $\omega_0 = 1.7003$ rad/s. Fig. 12 was produced by the $\Delta \omega$ against state trajectories at coordinates from $-1.6052$ to $+1.5679$ rad/s and from $-0.1157$ to $+0.7601$ rad for the $\omega_{\text{min}}$-$\omega_{\text{max}}$ and $\delta_{\text{min}}$-$\delta_{\text{max}}$, respectively. The results of the RNN model are depicted by red circles at coordinates from $-1.5110$ to $+1.6045$ rad/s and from $-0.1345$ to $+0.7457$ rad for the $\omega_{\text{min}}$-$\omega_{\text{max}}$ and $\delta_{\text{min}}$-$\delta_{\text{max}}$, respectively.

Fig. 13 shows the $\delta_L$ against $V_L$ state trajectories at coordinates from $0.0351$ to $0.2756$ rad and from $0.8290$ to $1.1119$ pu for the $\delta_{L\text{max}}$-$\delta_{L\text{min}}$ and the $V_{L\text{max}}$-$V_{L\text{min}}$, respectively. State trajectories of the RNN model can be depicted by red points at coordinates from $0.0342$ to $0.2613$ rad and from $0.8642$ to $1.1185$ pu for the $\delta_{L\text{max}}$-$\delta_{L\text{min}}$ and the $V_{L\text{max}}$-$V_{L\text{min}}$, respectively. The complete simulation results are tabulated in Table 4.

![Figure 11. The $\delta_L$-$V_L$ state trajectory when the DE at $\omega_0 = 1.6$ rad/s was applied](image1)

![Figure 12. The $\Delta \omega$ state trajectory when the DE at the value of $1.7003$ rad/s was applied to a power system](image2)
Figure 13. The $\delta_L-V_L$ state trajectory when the DE at the value of 1.7003 rad/s was applied to a power system

Based on the in Table 4 that the largest MSE was 17.8296, where the largest MSE was obtained on the speed rotor deviation ($\Delta\omega$) at the value of 1.7003 rad/s. Simulation results show that chaotic behavior of power systems can be modeled by the Elman recurrent neural network.

6. Conclusion

Chaotic oscillations in power systems using exact and RNN models are deeply studied in this research. The exact model was obtained using mathematical model. Then, the RNN model is obtained by training process using the data from exact model simulation. The training of the RNN model using adaptive learning rate both with and without momentum is compared. The performance of the adaptive learning rate with momentum is better than the other one. Chaotic behaviors are detected in power systems by appearing chaotic attractors both at power angle-rotor speed and at magnitude-angle voltage state trajectories in phase-plane.

7. Future Works

Chaotic behavior of power systems was an interest topic research in recent years. In the future, the chaotic behavior of power systems should be reduced and vanished by applying control strategy properly.

References


