Cellular Neural Network Based Situational Awareness System for Power Grids

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Abstract—Situational awareness (SA) in simple terms is to understand the current state of the system and based on that understanding predict how system states are to evolve over time. Predictive modeling of power systems using conventional methods is time consuming and hence not well suited for real-time operation. In this study, neural network (NN) based non-linear predictor is used to predict states of power system for future time instance. Required control signals are computed based on predicted state variables and control set points. In order to reduce computation the problem is decoupled and solved in a cellular array of NNs. The cellular neural network (CNN) framework allows for accurate prediction with only minimal information exchange between neighboring predictors. The predicted states are then used in computing stability metrics that give proximity to point of instability. The situational awareness platform developed using CNN framework extracts information from data for the next time instance i.e. a step ahead of time and maps this data with geographical coordinates of power system components. The geographical information system (GIS) provides a visual indication of operating status of individual components as well as that of the entire system.

I. INTRODUCTION

One of the key recommendations of the 2003 blackout report is the need for situational awareness in power system control centers [1]. Situational awareness in simple terms is to understand the current state of the system, and based on that understanding project how system states are to evolve over time. Recent developments have also evolved around the fact that information must be actionable. The development in utility control centers in recent years have evolved around better display systems. State of the art situational awareness (SA) systems have geographic information systems (GIS) as the front-end which aids in quicker absorption of information and hence better control actions.

Along with hurricanes, cascading failures are the major contributors to blackouts bigger than 5000 MW [2]. Changes in operating conditions cause stress. Protection relays which act locally, operate in order to relieve stress. In some cases, the operation of the relay, although beneficial for the local equipment might be detrimental for the system as a whole. Under such cases the increased stress level on other equipments results in their protective relays taking preventing measures to safeguard the equipment. This way one failure leads to another and thus the name cascading failure. Situational awareness, which aims to understand the current situation and project how system states are going to change in the future, plays an important role in prevention/mitigation of cascading failures.

This study aims to provide a general framework for power system predictive modeling. The non-linear predicting capabilities of NNs enable prediction for longer solution time-steps. In general, in a time-domain simulation numerical integration scheme is used. The numerical integration method works by linearizing small regions and essentially assumes states are going to change in a linear way between successive steps. For this assumption to be valid, the spacing between successive points i.e. solution time-step needs to be small. However, with the use of NNs i.e. a non-linear predictor, the permissible solution step-size is larger than in numerical integration schemes. Furthermore, a NN maps input to output. Since there is direct mapping, the inversion routine that is required for time-domain simulation can be circumvented.

In order to optimize performance with respect to computation, instead of using a single NN to compute all the states of a power system a cellular network structure is adopted. In the cellular neural network (CNN) framework, each cell represents a power system component, for example a generator is modeled by a NN. Cells are grouped together to form layers, each cell in a layer predicts the same state variable.

The framework is modular, meaning more cells and layers can be added. Since each cell only requires information from its neighbors, the architecture gives rise to a decentralized asynchronous learning framework [3], where learning happens based on need. Furthermore, since the problem is approximated by decoupling the states, it is possible to parallelize the task of prediction. This is a desirable property because in a realistically sized power network the number of state variables can reach tens of thousands. In order to be of practical use, the designed framework must be able to scale up linearly. The developed framework is linearly scalable because of the decoupled nature and it is possible to solve each cell as a thread in a multi-node graphical processing unit (GPU) accelerated device.

The developed situational awareness system based on CNN framework shown in Fig. 1 predicts state variables, a step...
ahead, by utilizing current and time delayed values of state variables. In addition, control signal for synchronous generator is computed by using the states that are of interest and their set points. The predicted states are then used to form stability metrics which gives more insight to the stability of the system and the distance to point of instability. The predicted states of the power system components are then mapped to their geographical coordinates.

The GIS system gives a visual indication of stability of system by means of color contour display. At the macroscopic level the developed geographical information system (GIS) gives visual indication of stability of the system, while at the same time also provides stability limits of individual assets at the microscopic level. The idea is that a scalable predictive modeling system with the aid of a GIS would give the control room operator much needed time to make informed decisions by predicting events before they happen. As such, a step ahead lead time of 100 ms is reported in this study.

The remaining part of this paper is divided into four sections. In Section II, an overview on cellular neural networks (CNN) is presented. This section deals with how a decoupled framework that is parallel in space is developed. Section III describes the application of the developed CNN framework for SA on New Zealand’s South Island reduced electrical system. In this section, specifics such as connectivity are discussed. Results and discussions cover Section IV. Conclusions are drawn and future work is discussed in Section V.

II. CELLULAR NEURAL NETWORK

There has been astounding improvement in the amount of computational power over the years. Today, an Intel i7 can perform $70 \times 10^9$ floating point operations per second and it consumes $< 100$ watts. Meanwhile the fastest supercomputer can perform about $10^{16}$ Flops per second. Although these are remarkable improvements they have not led to similar improvements when it comes to predictive modeling using time domain simulations. The limitation arises from the fact that a set of differential algebraic equations (DAEs) need to be solved in a sequential manner thereby limiting the use of parallel hardware. CNN framework is based on the concept of approximating solutions by decoupling them. Since the equations are decoupled they could be solved in parallel and hence the framework is linearly scalable.

In mathematical modeling of power systems, each system component is represented by a set of equations. For example, a third order model of a generator with a second order excitation system would require five first order differential equations. Other components are modeled in a similar manner and all of these equations are solved simultaneously. In CNN, each equation that is specific to a power system component is solved in a unit referred to as cell. A cell is a computational unit and provides its power system component state.

Groups of cells which perform the same function i.e. predict a state variable of the same type are grouped together to form a layer. For example, all the cells that predict speed deviation are grouped to form the speed deviation prediction layer. The idea here is that each cell can represent a specific state variable of a specific power system component and predict how that state variable is going to change from one time instance to the next, based on the current value of that state variable and the control signal applied to the component. In general, given a state variable $x(t)$ and control variable $u(t)$, $x(t + 1)$ can be predicted as follows,

$$\dot{x}(t + 1) = f(x(t), u(t))$$  \hspace{1cm} (1)

However, since all state variables are coupled, information from different parts of the system is required for prediction results to be correct. Hence the concept of connectivity is introduced. Connectivity is defined as the information flow between different cells. Take the case of speed deviation prediction, any change in the equilibrium between generation and load results in speed deviation. Speed deviation of a synchronous generator is influenced by inter-area as well as intra-area mode. Hence, instead of using speed deviation signal of all the generators in the system only the information from selective generators is used. This way each cell communicates with only a select group of cells. The concept of connectivity specific to the test system is explained in Section III. The multilayer perceptron (MLP) architecture with one hidden layer is used as computational unit in all cells.

III. SITUATIONAL AWARENESS USING CNN FRAMEWORK

The concept of a layer as explained previously is used to distinguish different types of cells. The layers are classified with respect to the state variable that is being predicted. The state variables predicted are speed deviation of generators, bus voltage, generator active power output, active power-flow through lines, transient stability margin and voltage stability load index. In this section, formulation for each state variable as well as connectivity is developed.

A. Test System

In this study, New Zealand’s South Island equivalent electric grid is used. An equivalent South Island system as shown in
B. Speed Deviation Prediction

Generators used in power systems are mainly synchronous machines, which means they operate at constant speed. Multiple generators operate in parallel and their output is combined because all of the generators produce power at the same frequency. Synchronism between a generator and the rest of the system or between a group of generators and the rest of the system will be lost if speed deviation is above certain prescribed limits.

It is important to ensure that step size is not too big or too small. Much like time domain simulation, higher step-sizes would result in higher accumulated errors and smaller step-sizes would result in more computation time. Also, the realistic rate of measurement is bounded by phasor measurement unit (PMU) reporting rate. With consideration to the afore mentioned facts, prediction is done 100 ms ahead of time i.e. a step size of 100 ms is used in this study. Speed deviation prediction is formulated as,

\[
\Delta \omega_i(t + 1) = f_\omega(\Delta \omega_i(t, t - 1, t - 2), \Delta \omega_n(t), \Delta V_{ref,i}(t))
\]

(2)

Speed deviation at current and time delayed instances i.e. t, t-1, t-2 are used as input to give the computational unit an idea of rate of change of the variable. \( \Delta \omega_n(t) \) is the speed deviation of neighboring generators i.e. the generators from which information is received. \( \Delta V_{ref}(t) \) is the difference between terminal voltage and its reference set point. ‘Connectivity’ used for speed deviation prediction is shown in Fig. 2. Here, each computational unit is superimposed on top of one line diagram to show how spatial dynamics are captured. Information flow is shown as directed lines.

Every generator in the system is going to influence every other generator in some way but the main goal is to capture all that information or most of it using a small number of connections. In other words, it is possible to capture all or most of the dynamics by using information from specific generators. The idea is based on decentralized asynchronous learning where information exchange is used by computational units for prediction. For example, the computational unit representing Tekapo generation plant has only one neighbor while most of the other generation plants have two. This is because all or most of the spatio-temporal information of generators in the system is captured by computational unit representing Ohau generation plant through its interconnection with other computational units and hence the input from Ohau generation plant is used to accurately predict speed deviation changes at Tekapo generation plant. Several combinations are formed based on knowledge of the system and the best possible combination is chosen, and is shown in Fig. 2. Table I shows cell dimensions for the speed deviation layer.

### Table 1: Cell dimensions for the speed deviation prediction layer

<table>
<thead>
<tr>
<th>Generator Name</th>
<th>Neural Network Structure (number of neurons in input × hidden × output layer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aviemore</td>
<td>5 × 10 × 1</td>
</tr>
<tr>
<td>Benmore</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Clyde</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Manapouri</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Ohau</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Roxburgh</td>
<td>7 × 14 × 1</td>
</tr>
<tr>
<td>Tekapo</td>
<td>5 × 10 × 1</td>
</tr>
</tbody>
</table>

C. Bus Voltage Prediction

Voltage changes at a bus are a result of changes in local loading/generating conditions. As a result, it is possible to predict voltage change at any given bus with the knowledge of bus voltage at that particular bus where prediction is to be carried out in addition to measurements from a few other neighboring buses. This way bus voltage prediction at each bus can be broken down into smaller problems and solved in a distributed framework.

There are two types of buses in the system, generator and non-generator buses. Generator buses are considered as a special case because they also require control signal as an additional input. In general, bus voltage prediction at generator and non-generator buses can be formulated as in (3) and (4). Here, \( V_i(t) \) is voltage at generator bus and \( V_j(t) \) is voltage at non-generator bus. \( \hat{V}_i(t) \) is the bus voltage of neighboring buses and \( \Delta V_{ref,i}(t) \) is the difference between terminal voltage and reference set point of the \( i^{th} \) generator.

\[
\hat{V}_i(t + 1) = f_{V_i}(V_i(t, t - 1, t - 2), \hat{V}_n(t), \Delta V_{ref,i}(t))
\]

(3)
\[ \hat{V}_j(t + 1) = f_{Vj}(V_j(t, t - 1, t - 2), \hat{V}_n(t)) \] (4)

Connectivity, as in the case of speed deviation layer, is formed with knowledge of the system. Several combinations are tried and the connectivity that yields best results is chosen. Table II shows the cell dimension for voltage prediction layer.

<table>
<thead>
<tr>
<th>Bus Name</th>
<th>Neural Network Structure (number of neurons in input × hidden × output layer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aviemore LV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Benmore LV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Clyde LV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Manapouri LV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Ohaaki LV</td>
<td>6 × 14 × 2</td>
</tr>
<tr>
<td>Roxburgh LV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Tekapo LV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Aviemore HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Benmore HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Clyde HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Manapouri HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Ohaaki HV</td>
<td>6 × 14 × 1</td>
</tr>
<tr>
<td>Roxburgh HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Tekapo HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Invercargill HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Tiwai HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Bromley HV</td>
<td>6 × 12 × 1</td>
</tr>
<tr>
<td>Islington HV</td>
<td>6 × 14 × 1</td>
</tr>
<tr>
<td>Livingstone HV</td>
<td>6 × 12 × 1</td>
</tr>
</tbody>
</table>

D. Generator Active Power Prediction

Generator active power is predicted as a function of active power at current and time delayed instances. In addition, difference between terminal voltage and reference set point of the generator is used as control input. Power generation of neighboring generators also result in changes. Hence, information from neighbors is also used. Active power prediction is formulated as,

\[ \hat{P}_i(t + 1) = f_P(P_i(t, t - 1, t - 2), \hat{P}_n(t), \Delta V_{ref,i}(t)) \] (5)

Neighbors are determined in the same way as discussed in speed deviation prediction and hence connectivity is the same as in the speed deviation layer.

E. Active Power-Flow Prediction

In modern power systems, transmission lines are operated close to their capacity in order to maximize profits and meet demand. It is therefore important to monitor line flows. Active power-flow between two buses I and K is predicted as follows,

\[ \hat{P}_{IK}(t + 1) = f_{IK}(P_{IK}(t, t - 1, t - 2), V_I(t), V_K(t)) \] (6)

\[ \hat{P}_{KI}(t + 1) = f_{PKI}(P_{KI}(t, t - 1, t - 2), V_I(t), V_K(t)) \] (7)

\( P_{IK} \) is the active power injected at bus I in the line connecting bus I and bus K. Similarly, \( P_{KI} \) is the active power injected at bus K in the line connecting bus I and bus K.

F. Transient Stability Margin

Power transfer between machines is a highly nonlinear relationship and it depends on the rotor angle deviation between machines. Until a certain value of angular separation power transfer increases. This angular separation results in inherent stability property of synchronous machines. Imagine a scenario where one generator is running faster than normal, this generator is connected to other generators in the system which are running at slower speed. Since increase in angular separation results in increased power transfer, some of the load of the slower running machines is transferred to faster running machine and gradually a steady state operating point will be reached.

However, if the angular separation between machines goes beyond a certain point the reverse happens and this leads to instability. Transient stability margin (TSM) gives the distance to that critical point. TSM has been studied using energy function method [5]–[7] and using one machine infinite bus equivalent [8]–[10]. In this study, TSM is calculated for each machine by finding angular separation between each generator and an equivalent model of the remaining generators using center of inertia (COI) method. It is formulated as

\[ \delta_{eq} = \frac{\sum_{i=1}^{n-1} H_i \cdot \hat{\delta}_i}{\sum_{i=1}^{n-1} H_i} \] (8)

\[ TSM_i = \hat{\delta}_i - \delta_{eq} \] (9)

In order to predict TSM, transient stability margin prediction layer predicts rotor angle deviation and from that equivalent rotor angle is computed using (8). TSM is then computed as defined in (9). The rotor angle prediction problem for TSM computation is formulated as given in (10) where \( \Delta V_{ref,i} \) is the difference between reference voltage magnitude and actual voltage magnitude of generator, \( \delta_i \) is the rotor angle of the generator and \( \delta_n \) is rotor angle of neighboring generator.

\[ \delta_i(t + n\Delta t) = f_\delta(\delta_i(t, t - 1, t - 2), \hat{\delta}_n(t), \Delta V_{ref,i}(t)) \] (10)

G. Voltage Stability Load Index

Voltage stability can be defined as the ability of power system to maintain acceptable voltage levels during normal conditions and during disturbance [11]. It has been found that voltage magnitude does not give a good indication of voltage stability limit. Many studies have been carried out to determine voltage stability indices in order to facilitate necessary control actions to preclude eminent instability and thereby improving voltage stability in a power system [12]. Reference [13] proposed local qualitative indices such as transmittance index, steady state stability index and loss sensitivity index. Reference [14] also used sensitivity technique to predict voltage collapse. A comprehensive comparison of existing methods is given in [15].

The one used in this study is based on a function of load and no-load voltage magnitude and angle \( V_L, \theta_L, V_0 \) and \( \theta_0 \) respectively. It is difficult to calculate voltage stability load index in real-time because no-load voltage is a function of loading at
different buses. At any given time, loading at buses are going to vary and hence a look-up table approach is not possible as number of combinations are large. Also, calculating no-load voltage requires power-flow calculation and this is difficult to obtain in a short span of time as the system is continually changing and hence the value calculated at last time instant is not accurate for current time instant. Voltage stability load index can be calculated with the following formula as give in [16],

\[
V_{SLI} = \frac{4(V_0V_t \cos(\theta_0 - \theta_L) - V_0^2 \cos^2(\theta_0 - \theta_L))}{V_0^2}
\]

Equation (11) results in a numeric value between 0 and 1. A value of 1 represents voltage collapse point. Hence, by calculating VSLI, distance to voltage collapse point can be identified and preventive control actions, if required could be taken. In this study, VSLI at a given bus is predicted using load bus voltage magnitude \(V_t\) and voltage angle \(\theta_t\) in the following way,

\[
\hat{V}_{SLI}(t + n\Delta t) = f_{vsli}(V_t(t, t - 1, t - 2), \theta_t(t, t - 1, t - 2))
\]

H. Geographic Information System

The Geographic information system (GIS) is developed in MATLAB. In the developed system all the generation plants as well as major load centers are mapped to their geographical coordinates. Currently, state of the art visualizations include contours, dials, pie charts, embedded charts, dynamic line formatting and spark lines. Traditionally these visualizations are used in tandem with a pseudo-GIS (one line diagram) system. However, the current trend is to use a true GIS system in tandem with the above mentioned forms of information display. Several software packages such as space-time insight and ORNL VERDE also provide the functionality of 3D display.

IV. RESULTS AND DISCUSSION

A. CNN - Training and Testing

NNs require historic data. There are two widely used class of methods for CNN training: forced and natural training [17]. In forced training, system is perturbed using pseudo random binary signal (PRBS). PRBS is a system identification technique where a noise signal of different frequencies is injected into controllers as supplementary signal. The controllers respond to the PRBS signal and thereby changes it control setting to cause perturbation in the system. In natural training, faults are applied and the resulting changes in the system are captured and are used for training. Testing methods are the same as training methods, however the generated data is new i.e. the data was never seen by CNN before. This way one can test whether system dynamics were actually learned by CNNs.

B. Discussion

A predictive approach is useful to analyze the propagation of stress through a system. The developed SA system is apt at learning changes in system and adjusts itself accordingly. Since a fault cannot be anticipated, predicted signals at the exact juncture of the event is not accurate as the SA system expected the power grid to continue operation in steady state. However, once change has been detected through field measurements the SA system immediately adjusts itself to alter its prediction and quickly follows the actual system conditions and predicts one-step ahead of time. This can be seen in Fig. 3.

The developed SA system is tested against a six-cycle three-phase fault at the Islington plant and predictions are compared with actual values to give a visual indication of performance. Numerical values are discussed in Table III. Three different metrics, mean squared error (MSE), root mean squared error (RMSE) and absolute relative error (ARE) are reported. Values are obtained on a normalized scale of 0 to 1. In Fig. 3 (a), a sudden increase in loading at Islington i.e. 25% increase in active power consumption from base case results in an increase in VSLI. Load increase is applied at \(t = 1.8\) seconds. In this particular figure, in order to prove tracking performance of VSLI layer, actual and predicted values are both plotted for time \(t\). The reason being, a load change cannot be predicted ahead of time and hence if VSLI for \(t + 1\) were to be predicted the change at that particular point when load is increased would be missed.

Hence, to illustrate tracking performance during sharp changes in operating conditions, prediction is shown for \(t\) instead of \(t + 1\). Results shown indicates slight mismatch between actual and predicted values of VSLI at both steady-state and during transients. The reason being, as stated in the previous section, the no-load voltage magnitude and angle are not available and CNN is trained under various operating conditions in order to facilitate learning without having the values of missing components. However, after having trained under several different operating conditions, an optimized value for no-load voltage magnitude and theta is ascertained by CNN that gives least error when applied under various conditions.

The relationship between no-load voltage magnitude and angle at a bus is a function of load variation across the system. Thus, unless system wide loading conditions are explicitly provided it would be impossible for the CNN to learn the required functional relationship. Hence, with the limitations in mind, the problem is formulated in such a way that VSLI can be predicted purely as a function of voltage profile at a given load bus. Hence, there is a slight variation between actual and predicted values at steady state and during transients.

Fig. 4 illustrates the importance of a visual display system. The prediction engine is complimented by a visual display system that maps critical power system components to geographical coordinates and gives a visual indication of their operating status as well as that of system.
Figure 3: Prediction results for a 6 cycle 3-phase fault at Islington 220 kV bus (a) Speed deviation prediction at Aviemore generation plant; (b) Voltage prediction at Tekapo 220 kV bus; (c) Power variation prediction at the Roxburgh generation plant; (d) Active power-flow prediction between Manapouri-Invercargill 220 kV bus; (e) Transient Stability margin prediction at the Tekapo generation plant. TSM is calculated using COI method; (f) VSLI variation at Islington 220 kV bus due to 25% increase in real power loading from base case.
Figure 4: (a) Difference in oscillation mode between Manapouri generation plant and other generation plants; (b) Close-up of sub-figure (a) showing the difference in frequencies between both areas; (c) Developed geographical information system that maps power system components to their geographical coordinates is shown. Speed deviation prediction results are used and this particular snapshot shows color contour of frequency deviation. Difference in frequency between different areas can clearly be seen.
Fig. 4 (a) shows the two different modes of the system where the Manapouri generation plant and the rest of the generation plants swing out of phase with each other. At about 6.5 seconds, the frequency deviation of the two areas are such that the Manapouri generation plant has a frequency below 50 Hz, while the other area has a frequency of above 50 Hz. This is clearly picked up by the GIS system and it becomes easier for control center operators to comprehend the different areas and act accordingly.

It is to be noted that the results shown are predicted ahead of time i.e. 100 ms. Future work is to extend the lead time thereby giving the control room operator much needed time that could potentially mitigate/prevent imminent blackouts. The developed module is flexible, meaning more layers to predict more state variables can be added if needed. Also, state variables that are predicted could be used for further analysis. For example, the speed deviation signal could be used to predict inter-area modes which could then be used to damp system oscillations.

### Table III: Performance of SA system

<table>
<thead>
<tr>
<th>Layer</th>
<th>MSE</th>
<th>RMSE</th>
<th>ARE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed Deviation</td>
<td>$3.925 \times 10^{-4}$</td>
<td>$1.981 \times 10^{-2}$</td>
<td>$6.373 \times 10^{-2}$</td>
</tr>
<tr>
<td>Voltage</td>
<td>$2.708 \times 10^{-3}$</td>
<td>$5.29 \times 10^{-2}$</td>
<td>$1.078 \times 10^{-1}$</td>
</tr>
<tr>
<td>Generator Active Power</td>
<td>$1.395 \times 10^{-3}$</td>
<td>$3.736 \times 10^{-2}$</td>
<td>$6.617 \times 10^{-2}$</td>
</tr>
<tr>
<td>Active Power-Flow</td>
<td>$1.544 \times 10^{-3}$</td>
<td>$3.91 \times 10^{-2}$</td>
<td>$8.622 \times 10^{-2}$</td>
</tr>
<tr>
<td>Transient Stability Margin</td>
<td>$8.053 \times 10^{-4}$</td>
<td>$2.837 \times 10^{-2}$</td>
<td>$5.242 \times 10^{-2}$</td>
</tr>
<tr>
<td>Voltage Stability Load Index</td>
<td>$1.48 \times 10^{-3}$</td>
<td>$3.847 \times 10^{-2}$</td>
<td>$8.27 \times 10^{-2}$</td>
</tr>
</tbody>
</table>

### V. CONCLUSION

An alternative approach for power system predictive modeling is presented in this study. System states are predicted by using current and time delayed values and control signal. Control signals are computed by using state variables and control set points. The predicted system states are used to compute metrics which give an indication of stress level of the system and the distance to point of instability. Feasibility of the developed system for predictive modeling is demonstrated on New Zealand’s South Island reduced electrical system. Furthermore, in order to facilitate faster absorption of information, a visual display system which maps critical power system components to geographical coordinates is developed. The developed geographical information system provides color contours of different state variables and metrics. A lead time of 100 ms is realized in this study. Future work will involve finding ways to increase lead time.

### REFERENCES


