Abstract—The continuing increase of demand for electrical energy has resulted in power grids being operated closer to its operating limits. At the same time, integration of renewable energy sources introduces conditions of high uncertainty and high variability. Maintaining power system reliability under these conditions is a challenging task. Development in telecommunications and other advances have enabled more accurate and faster influx of data. However, more data does not equate to more information. With the plethora of data available it becomes necessary to extract information that a control room operator can act upon. Situational awareness (SA) in simple terms is to understand the current state of the system and based on that understanding project how things are to evolve over time. The situational awareness platform presented in this paper extracts information from data for the next time instance i.e. a step ahead of time and maps this data with geographic coordinates of utility assets. The geographic information system (GIS) provides a visual indication of health of individual units as well as that of the entire system.

Index Terms—Geographical information system, situational awareness, wide-area monitoring.

I. INTRODUCTION

One key recommendation of the 2003 blackout report is the need for situational awareness [1]. Situational awareness in simple terms is to understand the current state of the system and based on that understanding, to project how things 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 among others. 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 causes for blackouts bigger than 5000 MW [2]. Changes in operating conditions causes 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 things are going to change in the future, plays an important role in prevention or mitigation of cascading failures. The general idea of situational awareness is presented in Fig. 1.

Figure 1: Situational awareness in power grids

This study aims to provide a general framework that could be extended to perform multi-step predictive modeling of power systems. This would enable prediction for extended lead times. Such a system, when realized, would give a visual indication of stability of system at the macroscopic level while at the same time also provides stability limits of individual assets at the microscopic level. The idea is that such a system would give the control room operator much needed time to make informed decisions. The GIS system, which is the front-end of the SA system, will allow faster understanding of system states. As such, a step ahead lead time of 100 ms is reported in this study.

In section II, a detailed breakdown on cellular computational networks (CCN) 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 CCN 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
II. CELLULAR COMPUTATIONAL NETWORK

There has been astounding improvement in the amount of computational power over the years. In 1990, the fastest supercomputer in the world, Cray-2 could perform 1.9 GFlops per second i.e. $1.9 \times 10^9$ floating point operations per second. Today, an Intel i7 can perform $70 \times 10^9$ floating point operations per second and it consumes < 100 watts and is less than one square inch in area. Meanwhile the fastest supercomputer to date, Blue Gene can perform about $16 \times 10^{15}$ Flops per second and has more than one and a half million cores. 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) needs to solved in a sequential manner thereby limiting the use of parallel hardware. CCN is based on the concept of approximating solutions by decoupling them. Concepts and terminologies used are explained in the following subsection.

In mathematical modeling of power systems, each system component is represented by a set of equations. For example, a fourth order model of a generator with a second order automatic voltage regulator (AVR) would require six equations. In a similar manner other components are modeled and all of these equations are solved simultaneously. In CCN each set of equations that are specific to a power system component are solved in a unit referred to as cell. A cell is a computational unit that represents a power system component. With respect to the example presented above, a cell that models a fourth order generator with a second order AVR would have six equations.

If a time domain approach is followed, there are ways to decouple the system [3] and each of the decoupled equations can then be modeled accordingly in terms of cells and solved separately in parallel processors thereby providing speedup. An alternative approach is presented in this study, wherein instead of representing the cells with a set of equations to model a power system component, each cell is a neural network (NN) that has been trained with historic data. Neural networks are known to be good at function approximation and they can map input to output from historical data.

Groups of cells which perform the same function 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 this time instance to the next based on current value of that state variable and control signal. In general, given a state variable $x(t)$ and control variable $u(t)$, $x(t + 1)$ can be predicted as follows,

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

However, since all state variables are coupled, information from different parts of the system is required for prediction results to be more accurate. 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 has 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.

III. SITUATIONAL AWARENESS USING CCN FRAMEWORK

The concept of a layer as explained previously is used to segregate 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 prediction, 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. Speed Deviation Prediction

Generators used in power systems are 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. Also, as the frequency of the generators reaches certain levels, they reach their resonant frequency at which the rotor blades can be permanently damaged or even shattered.

Speed deviation can arise as a result of difference between load and generation. In power systems operation, generation is controllable but only minimal control of loads exist to this date through demand response. Hence, load forecast for a window...
of time, usually 15 to 30 minutes is done and dispatch is carried out based on forecast. However, in reality loads vary during this time causing a difference between generation and demand. Different modes of oscillation can result from such a condition.

Modes of oscillation could be intra-area or inter-area. Intra-area oscillations occur when a group of generators swing together. When there is a change in loading, angular separation between machines vary accordingly to transfer required amount of power. Consider a case where one generator is running faster than normal, with an increase in angular separation more electrical power is transferred from this machine or it could be viewed as load being shifted from other generators within the group to the machine running faster. This way, the group of machines tied together transfer load among themselves until a stable operating condition is reached.

However, power transfer as a result of angular separation is a highly nonlinear function and after a certain point, increase in angular separation results in decrease in power transfer and eventually results in synchronous machine falling out of step i.e. losing synchronism with the rest of the machines. This phenomenon is referred to as transient stability. Intra-area oscillations is a result of the phenomenon discussed above and occurs between machines within a group while inter-area oscillations is between groups of generators. Hence, it is clear, at this point, that speed deviation is an important state variable that needs to be predicted in advance such that corrective measures can be taken to ensure system stability.

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

Speed deviation at current and time delayed instances i.e. t, t-1, t-2 is used as input to give the computation 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 with which information is received from. \( \Delta V_{ref}(t) \) is the change in field voltage reference set point. ‘Connectivity’ used for speed deviation prediction is shown in Fig. 4. 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 has only one neighbor in Ohau while most of the other generating units 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 through its interconnection with other computational units and hence the input from Ohau is enough to accurately predict speed deviation changes at Tekapo. Several combinations are formed based on knowledge of the system and the best possible combination is chosen and is shown in Fig. 4.
B. 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,

\[ V_g(t+1) = f(V_g(t, t-1, t-2), V_n(t), \Delta V_{ref,g}(t)) \]  (3)

\[ V_{ng}(t+1) = f(V_{ng}(t, t-1, t-2), V_n(t)) \]  (4)

Here, \( V_g(t) \) is voltage at generator bus and \( V_{ng}(t) \) is voltage at non-generator bus. \( V_n(t) \) is the bus voltage of neighboring buses and \( \Delta V_{ref} \) is change in field voltage reference set point. 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.

C. Generator Active Power Prediction

Active power is predicted as a function of active power at current and time delayed instances. In addition, speed deviation and change in field voltage reference set point is used as control inputs. Power generation of neighboring generators also result in changes. Hence, information from neighbors are also used. Active power prediction is formulated as,

\[ P_i(t+1) = f(P_i(t, t-1, t-2), P_n(t), \Delta \omega_i(t), \Delta V_{ref,i}(t)) \]  (5)

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

D. 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 buses I and K is predicted as follows,

\[ P_{IK}(t+1) = f(P_{IK}(t, t-1, t-2), V_I(t), V_K(t)) \]  (6)

\[ P_{KI}(t+1) = f(P_{KI}(t, t-1, t-2), V_I(t), V_K(t)) \]  (7)

Here, subscripts I and K represent bus I and bus K. \( P_{IK} \) is the active power injected at bus I in the line connecting bus I and bus K. In the same way \( P_{KI} \) is the active power injected at bus K in the line connecting bus I and bus K.

E. 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 [4]–[6] and using one machine infinite bus equivalent [7]–[9]. 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

\[ \delta_{eq} = \sum_{i=1}^{n-1} H_i \cdot \delta_i \]

\[ TSM_i = \delta_i - \delta_{eq} \]  (9)

In order to predict TSM, transient stability margin prediction layer predicts rotor angle deviation and from that TSM is calculated mathematically as defined in (9) using center of inertia (COI) method.

F. 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 [10]. 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 [11]. Reference [12] proposed local qualitative indices such as transmittance index, steady state stability index and loss sensitivity index. Reference [13] also used sensitivity technique to predict voltage collapse. Reference [14] uses eigenvector of Jacobian matrix.

Reference [15] gives a scalar number to each load bus. The so called L-index is a number between 0 and 1 and indicates the proximity to voltage collapse. [16] gives a simplified procedure used for L-index calculation. Recently, singular value decomposition of PMU data has been used as an indicator. The method views physical power system as a power flow solver - taking time varying loads/injections as inputs, and producing PMU-measured angles and voltage magnitudes as outputs. By observing a time window of PMU measurements it can be seen that outputs vary much more dramatically when the system is
highly stressed. Hence, one of the outputs of SVD based PMU processing algorithm serves as a real-time indicator of system stress, tracking a well established voltage stability performance metric without the need for detailed network parameter values or state estimator results [17]. A comprehensive comparison of existing methods is given in [18].

The one used in this study is based on a function of no-load and load voltage. 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 [19],

\[ VSLI = \frac{4(V_0V_L\cos(\theta_0 - \theta_L) - V_L^2\cos^2(\theta_0 - \theta_L))}{V_0^2} \] (10)

Equation (10) 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.

G. Geographic Information System

The Geographic information system (GIS) is developed in MATLAB. In the developed system all the generating stations 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. Test System

In this study, New Zealand’s South Island equivalent electric grid is used. An equivalent South Island system as shown in Fig. 3 is modeled in RSCAD, the front-end for real-time digital simulator (RTDS). There are seven separate generating stations where each station has a number of generators. An aggregated model for generating stations is used i.e. all the generating units in a generating station are aggregated to form a single unit. There are 19 buses, seven loads and 24 transmission lines. All the lines are rated at 220 kV. The generating station Clyde is located on a fault line. Here, fault line refers to a surface trace of a fracture plane in the underlying rock along which a fault event is likely to happen i.e. an earthquake prone zone. The system is taken from [20] and modified to include Clyde generating station. The system is modeled with full transient dynamics.

B. CCN - Training and Testing

NNs require historic data. There are two widely used class of methods for training: forced and natural training. 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 NN before. This way one can test whether system dynamics were actually learned by NNs.

C. Discussion

A predictive approach is useful to analyze the propagation of events through the system. The developed SA system is apt at learning changes in system and adjusting itself accordingly. As an example, Fig. 5 shows close-up of prediction exactly at the moment of a short-circuit event. 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.

The developed SA system is tested against a six-cycle three-phase fault at Islington and predictions are compared with actual values to give a visual indication of performance. Numerical values are discussed in Table I using several metrics where values are obtained on a normalized scale of 0 to 1. Voltage stability load index results presented in Fig. 6 (f) is for 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 4 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.

![Figure 5: Adaptability of CCN after a sudden change in operating condition](image_url)
Figure 6: (a) Speed deviation prediction at Roxburgh generating station following a 6 cycle 3-phase fault at Islington; (b) Voltage prediction at Tekapo 220 kV bus following a 6 cycle 3-phase fault at Islington; (c) Power variation prediction at Roxburgh generating station following a 6 cycle 3-phase fault at Islington; (d) Active power-flow prediction between Manapouri-Invercargill following a 6 cycle 3-phase fault at Islington; (e) Transient Stability margin prediction at Tekapo generating station following a 6 cycle 3-phase fault at Islington. TSM is calculated using COI method; (f) VSLI variation at Islington due to 25% increase in loading from base case.
Figure 7: (a) Difference in oscillation mode between Manapouri and other generators; (b) Close-up of sub-figure (a) showing the difference in frequencies between both areas; (c) Developed geographical information system that maps assets 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. 7 illustrates the importance of a visual display system. The prediction engine is complimented by a visual display system that maps utility assets to geographical coordinates and gives a visual indication of health of individual assets as well as that of system. The test system has two areas, the generating station at Manapouri is one and the rest of the generators form the second area. Fig. 7 (a) shows the two different modes of the system where Manapouri and the rest of the generators swing out of phase with each other. At about 6 and a half seconds the frequency deviation of the two areas are such that Manapouri 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 I: Performance of SA system

<table>
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<th>Layer</th>
<th>MSE</th>
<th>RMSE</th>
<th>ARE</th>
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<td>1.98 x 10^{-2}</td>
<td>6.373 x 10^{-2}</td>
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<tr>
<td>Voltage</td>
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<td>Generator Active Power</td>
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<td>3.736 x 10^{-2}</td>
<td>6.617 x 10^{-2}</td>
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<tr>
<td>Active Power-Flow</td>
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<td>3.93 x 10^{-3}</td>
<td>8.622 x 10^{-2}</td>
</tr>
<tr>
<td>Transient Stability Margin</td>
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<td>2.837 x 10^{-2}</td>
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<td>1.138 x 10^{-2}</td>
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### V. CONCLUSION

As power grid is pushed closer to its operating limit it becomes important to move from reacting to a situation to being proactive. To do so the key is predictive modeling. Predictive modeling using time domain simulation is limited by the coupled nature of differential algebraic equations used to model power system. An alternative approach is proposed in which a cellular computational framework with neural networks as computational units is introduced. Feasibility of the developed system is demonstrated on New Zealand’s South Island reduced system. Furthermore, in order to facilitate faster absorption of information, a visual display system which maps utility assets 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 while at the same time providing relatively accurate results with respect to look ahead time.

### REFERENCES


