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Synchrophasor Data Driven Situational Intelligence for Power System Operation

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SUMMARY

With the emerging innovations to the electricity infrastructure, high levels of penetration of renewable energy, and an emphasis on competitive pricing, it will become necessary to optimize the safety margins presently allowed, and use existing equipment as optimally as possible. Maintaining reliable service and implementing emergency defense plans during major unintended disturbances and intended attacks is critical with the growth of the electric power network and its information infrastructure. The development of reliable and scalable intelligent monitoring and control algorithms, and situational intelligence (*beyond situational awareness (SA)*) technologies are needed as synchrophasor measurement devices are deployed for operation sense-making, decision-making and implementing actionable controls. The synchrophasor data can be used in model validation, improving models used in state estimators, and many EMS applications. Situational intelligence allows for real-time monitoring and faster than real-time simulation of power system operation. This paper presents online near-real-time and predictive applications of synchrophasor data in transmission control centers.

KEYWORDS

Control Centers; Power System Operations; Situational Intelligence; Synchrophasors.

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INTRODUCTION

The electric power grid operation is always under changing operating conditions – every second, minute and hour of the day. This is driven today by the changes in demand which instantaneously changes electric power generation resulting in dynamic changes in power flows, voltages and currents, across the entire interconnected electric power grid. It is well known, and proven by the number of power system blackouts that have occurred in recent years, that modern power systems are often less secure than systems of the past. The reasons for this are several and include the reduced investment in transmission infrastructure over the last twenty-five years, the proliferation of "economically sited" independent power producers, unusual power transfers driven by market activities, the use of complex controls and special protection systems (SPS), and a general lack of system-wide oversight regarding reliable planning and operation. It may be known that SPS have prevented blackouts in other parts of the world; the Eastern Interconnection in North America has suffered some blackouts from the failure of SPS [1].

The above mentioned problems cannot be addressed quickly or without significant financial investments and as a result, operators facing increasing security challenges are looking for innovative solutions to improve system operations in a timely and affordable manner. The primary challenging responsibility for the operators in the control centers is to maintain the integrity of grid which means ensuring that the operating conditions of various elements of the grid are safe, not violating any safety limits, or at minimal risk of losing any critical elements if any unforeseen contingency had to occur, while still meeting generation requirements for the ever-changing customer demand. The 1965 and 2003 blackouts of the North American power grid identified the need for control centers to be equipped with visualization displays and situational awareness tools to provide system operators with enhanced view of the real-time grid conditions of the large electrical interconnection.

Situational awareness (SA) is the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future [2, 3]. SA is an intermediate process in assessing the status of the system in order to make intelligent decisions for future development [4]. Sense-making is related to situational awareness and it is pointed out in [5] that SA combined with understanding leads to sense-making. Intelligent sense-making is essential for maintaining and enhancing the stability, security and safety of smart grid [6]. In [7], Greitzer et al. provide a sense-making perspective on situational awareness in power systems operations which is distinct from traditional human factors research, and focuses on clarifying priority, rather than volume, of data for decision making. It is a common consensus that wide area monitoring and control is vital to situational awareness (SA) in smart grids [8, 9]. More recently the rapid integration of renewables sources of energy such as wind and solar, and energy storage, and the online streaming of big data has accelerated the need for improved real-time power system operations in control centers.

Situational intelligence (SI) is seeing ahead how the situations will unfold over time. In other words, SA systems present situations based on some measurements of current states at time t. Whereas, SI uses SA at time t and predictions of future states to predict SA for a time $t+\Delta t$. Control centers need to handle big data, variable generation and a lot of uncertainties, and will need SI, that is to derive SA (information, knowledge and understanding) at time t and project it into time $t+\Delta t$. This paper presents online near-real-time (coherency analysis) and predictive (voltage stability load index) applications of synchrophasor data in transmission control centers.

SITUATIONAL INTELLIGENCE

Deriving information from phasor measurement unit (PMU) and other sensor data, knowledge from information and understanding from knowledge are important characteristics needed to realize situational intelligence (Fig. 1). Situational awareness present understanding of system states in context of time and space, and provides near-term projections of the states. Decision-making in real-time is critical since secure information and time is limited, and consequences of incorrect decisions will have adverse effects. Therefore, fast adaptive/robust tools are needed.

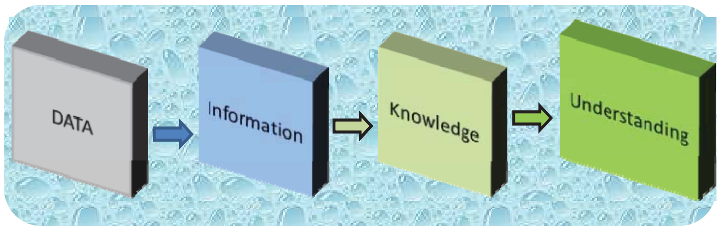

Fig. 1. Transformation from Data to Information to Knowledge to Understanding.

Situational intelligence is beyond situational awaremess (Fig. 2). It uses predictive modeling tools based on current and past measurements to infer future states, information, knowledge and understanding. Based on available computational capabilities, the prediction time step can be in order of fractions of seconds, few seconds, fractions of minutes, few minutes, etc. Realization of situational intelligence in transmission systems control centers for assistance in real-time operations will require specialized computational paradigms and implementations including high-speed parallel processing platforms to satisfy real-time requirements.

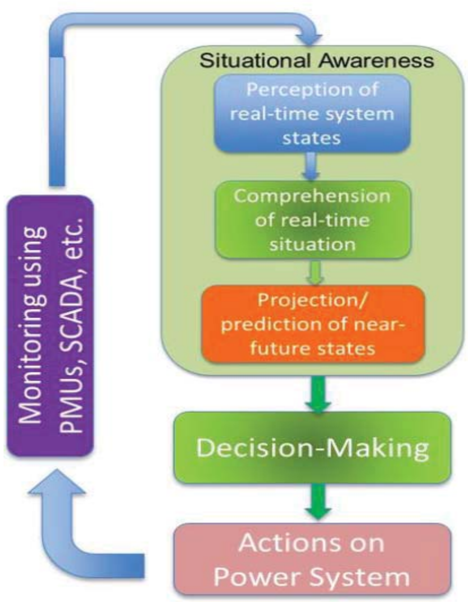

Fig. 2. SA system and its integration into power system operations.

SI APPLICATIONS IN TRANSMISSION CONTROL CENTERS

Some key challenges associated with real-time stability assessment in power systems [1, 10] are: the large numbers of contingencies and the sequence of events typically needed to provide accurate stability assessment; the wide range of operating conditions and topology of the power system (smart grid), which makes the operating space very complex; the speed by which the stability assessment can be assessed in real-time; the large number of measurements available in the power system; the lack of methods to enhance the correlations between measurements and the stability assessment; the lack of an effective assessment index; and meaningful system operator visualizations.

With the synchrophasor deployment in many utility networks, data from phasor measurement units is available for SI implementation. PMU data is transmitted to phasor data concentrators (PDCs) and, may be to a super PDC(s), as shown in Fig. 3. Applications are executed either at the PDC (control center), super PDC (ISO) or both. The transmission of data from the respective PMU stations to the control centers will acquire some communication latency and the application execution will increase the latency. Therefore, the presentation of data, information or knowledge in a control center to a system operator is post-real-time of the system status or event. Thus, today there is no real-time monitoring capability in control centers. With SI technology implementations, real-time monitoring is possible.

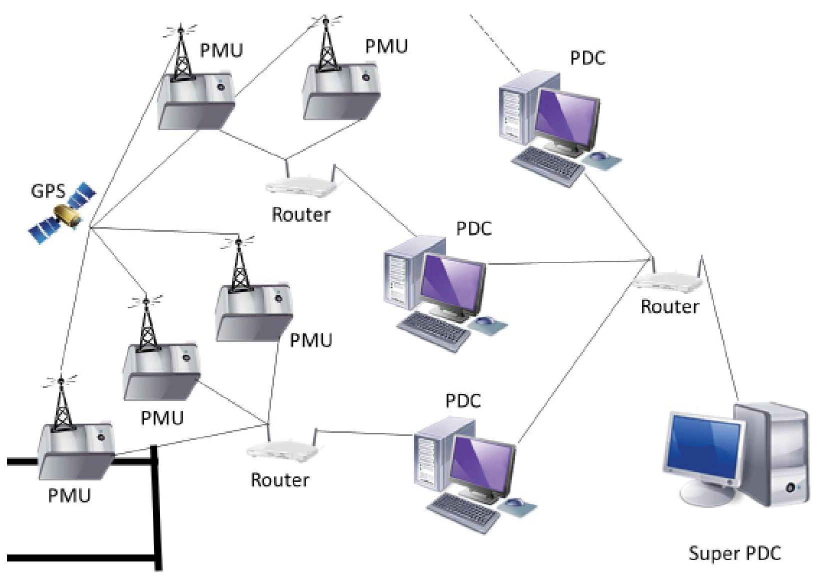

Fig. 3. Synchrophasor network for monitoring electric power system operation.

Online Voltage Stability Monitoring

Voltage stability monitoring in smart grids based on data from phasor measurement units has been developed. The method used estimated the voltage stability load index (VSLI) using a recurrent neural network (RNN) known as the echo state network (ESN). It has the power of a RNN but simpler learning requirements. Echo state networks have been trained with ease and precision without changing the weights between hidden-layer and input-layer.

A typical ESN structure is shown in Fig. 4. An ESN includes input, hidden (internal) and output layers with different transfer functions (linear, sigmoidal, etc.). Like the RNNs, the input vectors are fed into the neural network together with the last output from hidden layers. For example, when $u(t+1)$ is an input vector at time step $(t+1)$, activations of internal units, $x(t+1)$, are generally updated according to

$$x(t+1) = f(W^{in}.\ u(t+1) + W \cdot x(t) + W^{back} \cdot y(t)). \tag{1}$$

Where $f = (f_1, \ldots, f_n)$ are the internal unit's activation functions (sigmoids, etc.), W, W^{in} and W^{back} are hidden-hidden, input-hidden and output-hidden connections' matrices respectively and y(t) is the output of the ESN. For the study carried out in this paper, there are no output-reservoir connections and that means W^{back} is zero in (1).

Output units, $(y(t+1))$, are used to extract interesting features from this rich "reservoir" of dynamics, thus only "reservoir"-output connections, W^{out}, are modified during the learning/training process. The generic output of the ESN is given as

$$y(t+1) = g(W^{out}(u(t+1), x(t+1))). \tag{2}$$

where $g(.)$ consists of sigmoids or tanh functions. All reservoir weights can be chosen at random. For the studies on this paper, there is no input–output direct connection and the output of the ESN is given as

$$y(t+1) = g(W^{out}, x(t+1)). \tag{3}$$

Since the structure of ESNs is similar with that of RNNs, the same procedure can be followed to train the ESNs. However, by fixing a priori the recurrent network connections and adapting only a feedforward read-out network, ESNs have the advantage of overcoming the difficulties in RNN training [11].

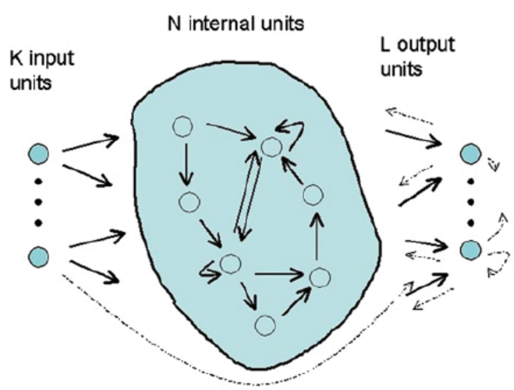

Fig. 4. A typical ESN architecture with input layer, hidden (internal) layer and output layer.

The VSLI estimation using ESN was studied on a modified IEEE 68-bus 16-machine power system with a large wind farm and distributed SmartParks (Fig. 5). SmartParks are plug-in electric vehicle parking lots with the capability to allow for vehicles to charge and discharge their batteries. The structure of the ESN for VLSI estimation for the IEEE 68 bus power system is shown in Fig. 6. With this architecture, it is possible to provide VLSI estimation at all the load buses in Fig. 5 for both normal and islanded operating conditions. For normal conditions a single ESN is used with the switch position at 1. In the case of islanded mode of operation the switch position is at 2, and individual ESNs provide the VLSI estimates for the respective load buses in each island.

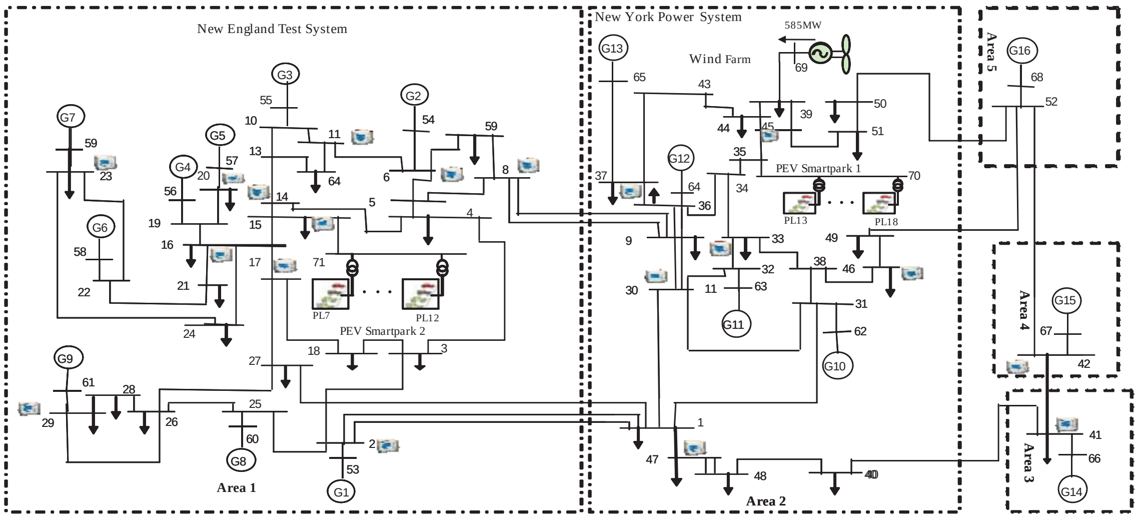

Fig. 5. A modified IEEE 68-bus power system with a wind farm and SmartParks.

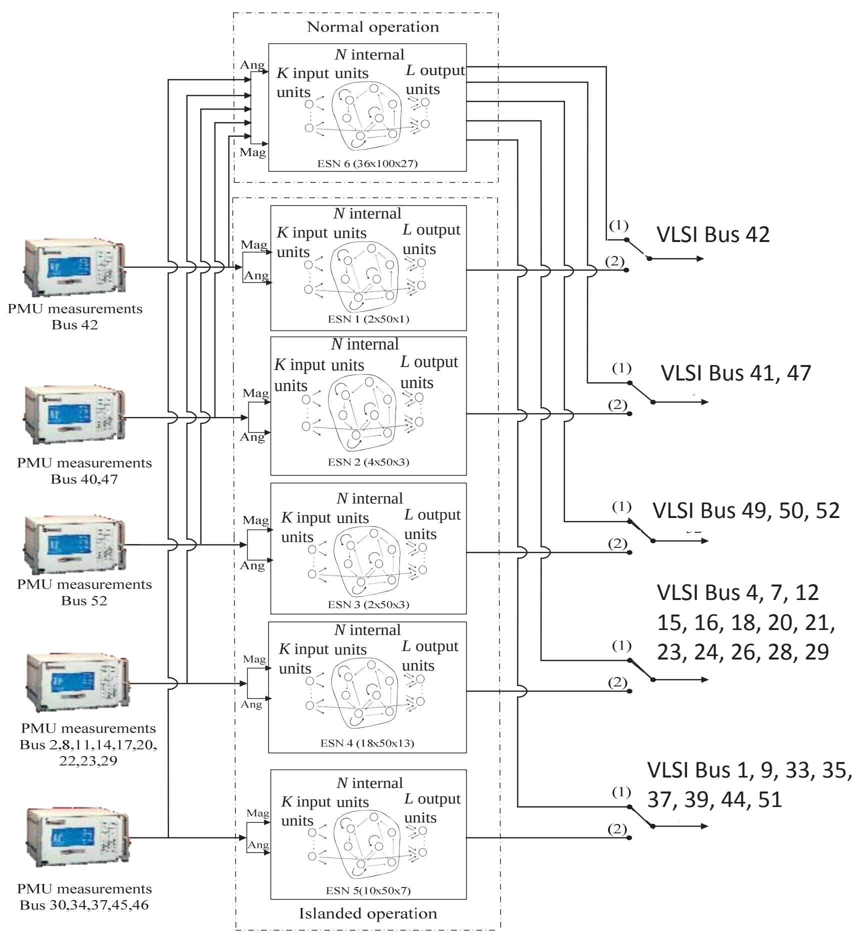

Fig. 6. Structure of ESN for VSLI estimation under normal and islanded operating conditions for the IEEE 68 bus power system.

Fig. 7 shows that the ESN approach successfully estimates the VSLI in a smart grid for load variations caused by the PEVs, mainly due to charging and discharging of a large number of plug-in electric vehicles. The top graph shows the PEV initially charging (-ve power) and gradually entering into the discharging mode (+ve power). The estimated VSLI at three buses (35, 39 and 44) are shown. Bus 39 is load bus in close proximity to the wind farm bus. Bus 35 is the PEV bus and Bus 44 is load bus between the Bus 39 and Bus 35. It can be observed that as the PEV discharges the VSLI becomes lower at these buses compared to when it was charging.

During this simulation the loads at the remaining buses were fixed. In a production (practical) power system it is possible for several load buses to experience load variations concurrently. The presented ESN approach in Fig. 6 will still work since measurements from PMUs at all the load buses are available as inputs to the ESNs.

More details on this application can be found in [12].

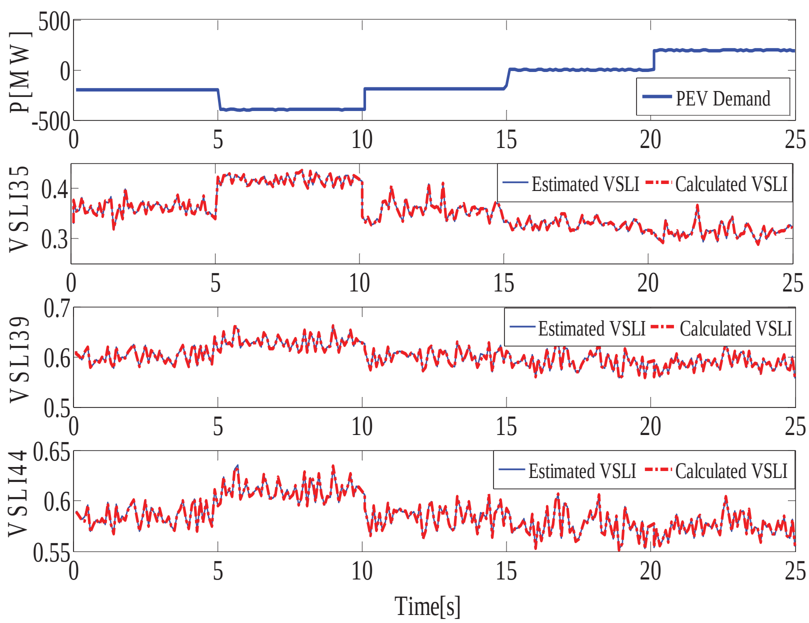

Fig. 7 ESN estimation of VSLI index with varying PEV demand.

Online Coherency Analysis of Synchronous Generators

In multi-machine power systems, synchronous generators tend to oscillate in several coherent groups, each group being equivalent to a virtual generator. Coherency analysis is fundamental to wide area control of large power systems. Coherency analysis is performed offline and the groupings are used in the development of auxiliary control signals. However, in response to various events at different operating conditions, the coherent groups may differ, and it has been observed that post disturbance during the transient the generators switch groups. Thus, it is important to develop the analysis to be online and be able to recognize the switching of groups by the generators in the network. A combination of *K*-harmonic means clustering (KHMC) and a moving windowing approach have been applied for online coherency grouping based on real-time speed data from PMUs located at generator stations [13]. For a 100ms three phase short circuit applied at bus 8 (Fig. 8) and based on the speed deviations of generators, the algorithm described in [13] showed that generators switched groups during the post-disturbance recovery (see Table I for the groups and its members at the respective time instances).

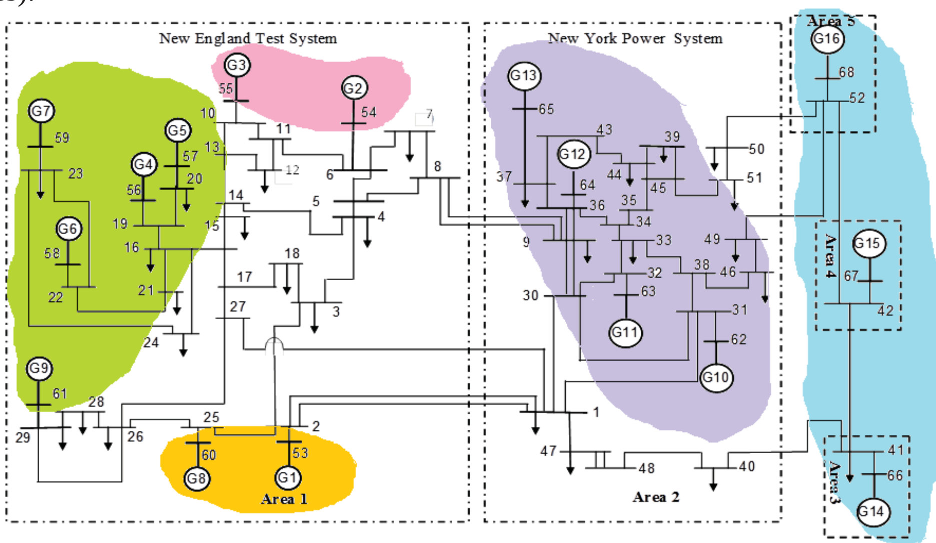

Fig. 8 . IEEE 68 power system with coherency results (color shades) shown based on an offline approach.

TABLE I: COHERENCY GROUPING RESULT

Group index	Offline Clustering during 0~18s	Online Clustering at 8s	Online Clustering at 10s	Online Clustering at 15s
1	G1, G8	G1,G8	G1,G2,G3, G8,G10,G11,G12,G13	G1,G8
2	G2,G3	G2,G3	G4,G5,G6, G7,G9	G2,G3
3	G4,G5,G6, G7,G9	G4,G5,G6, G7	G14,G15, G16	G4,G5,G6, G7,G9
4	G10,G11	G9		G10,G11, G12,G13
5	G12,G13	G10,G11		G14,G15, G16
6	G14,G15, G16	G12,G13		
7		G14,G15, G16		

For a production power system the generators' frequency data obtained from the PMU is available in control centers through a phasor data concentrator such as OpenPDC. The frequency/speed data can be pre-processed, if necessary, and applied to the online KHMC coherency algorithm. The data presented in Table 1 above can be viewed in a real-time control center using an advanced visualization such as that shown in Fig. 9. Fig. 9 is a snapshot of a movie. This visualization was developed by the Real-Time Power and Intelligent Systems Laboratory researchers at Clemson University [14]. The essence of this display on online coherency grouping is to alert the system operators of any abnormal oscillations that may arise in the system when under stress. Adverse interaction by power system stabilizers or predetermined wide control signals could rise in a multimachine power system when coherency of generators are not correctly identified when designing oscillation damping controllers.

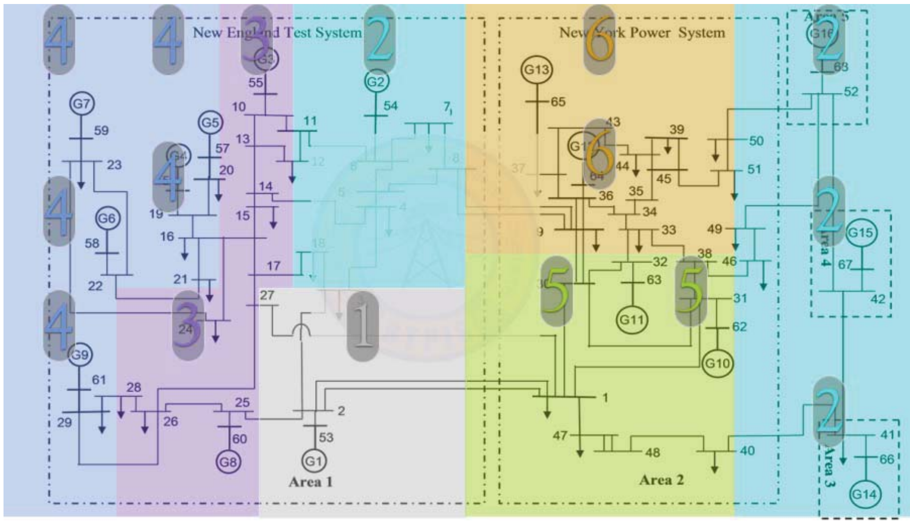

Fig. 9. A real-time visualization display for coherency grouping.

CONCLUSION

Intelligent systems that increase the abilities to plan in near-real-time, to learn, to understand complexity, to share understanding across neighboring/wide areas, and to take appropriate actions to ensure system stability and security are needed in smart grid’s transmission and distribution control centers. Situational intelligence based on PMU data will provide real-time monitoring and faster than real-time simulation of power system operation. System operators in real-time control centers will benefit from SI implementations and visualizations for making intelligent time critical decisions. Besides assisting system operators, SI will transform automatic control systems to their next level of performance.

ACKNOWLEDGEMENT

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