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Computational Approaches for Bad Data Handling in Power System Synchrophasor Networks

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Abstract: The state estimators used in real-time power system control centers now process bad data as a standard routine. With the introduction and deployment of phasor measurement units (PMUs), it is possible to model power systems, even with their time-varying nature, in real-time. However, PMUs remain vulnerable to providing bad data for several reasons. In this paper, a new intelligent framework, the cellular computational network (CCN), is introduced for the decentralized predictive modeling and dynamic state estimation (DSE) of a power system with PMU data. The CCN-based DSE is resilient to interactions between multiple segments of bad data from one or more PMUs.

Keywords: Bad Data, Phasor Measurement Units, Power System, Synchrophasor Network

1. INTRODUCTION

State estimation (SE) is the process of assigning a value to an unknown system state variable based on measurements from that system according to some criteria. As power systems become increasingly stressed and growing market activities cause rapid power flow changes, system operators must make decisions based on an accurate real-time model of the power system derived in a timely manner using SE. Many applications in real-time control centers depend on SE, including energy management systems (EMS), automatic generation control, contingency analysis, economic dispatch, load forecasting and optimal power flow. The weighted least squares (WLS) estimation method is the most commonly used technique in power system SE.

In order for the state estimator to estimate the state variables accurately, it must be provided with both accurate measurements and an accurate network model (Mili et al., 1985). The network model, which consists of the network connection model and network parameter models, is assumed to be known in the SE problem. The network topology and parameters may be erroneous. For example, in one well-known instance, the WLS state estimator failed to converge due to the existence of a topological error, indirectly contributing to the August 2003 blackout of the northeastern United States.

The SE methods commonly used today are very sensitive to bad data (Mili et al., 1985). Bad data detection involves determining whether the measurement set contains any bad data. Bad data usually are classified based on the type, location and number of measurements containing an error. Broadly, errors are classified as single bad data, meaning that only one measurement in the set of measurements has a large error, or multiple bad data, which are further classified as multiple either interacting or non-interacting bad data.

A system's state can be estimated indirectly in the presence of bad data using mathematical and intelligent computational approaches. The process involves detecting, identifying and removing bad data. Examples of mathematical approaches include the chi-square distribution test, the largest normalized residual test, and hypothesis testing identification. Intelligent computational methods, including heuristic methods, require either intensive training under different conditions or computationally demanding methods (Khwanram and Damorongkulkamjorn, 2009; Asada et al., 2005).

The integration and increasing penetration of renewable energy sources into the power grid demands the use of dynamic state estimation (DSE) that can model the time-varying nature of the power system (Arminifar et al., 2014). The introduction and deployment of phasor measurement units (PMUs) makes it possible to obtain synchronized phasors, the frequency and the rate of change of frequency (ROCOF) at 25/30 samples per second, or higher. These measurement devices allow for DSE. Adding PMU data to existing SE improves its reliability and robustness (Wu and Giri, 2006). However, PMUs remain vulnerable to providing bad data for several reasons including measuring equipment and communication channel failures, and cyber-attacks (Beasley et al., 2014)

In this paper, a new intelligent framework, the cellular computational network (CCN), is introduced for decentralized predictive modelling and DSE of a power system from synchrophasor data. It is shown that the CCN-based DSE is resilient to single and multiple interacting and non-interacting bad data from one or more PMUs.

2. CELLULAR COMPUTATIONAL NETWORK

A CCN (Fig. 1) is a framework that may contain several layers (1 to N) of computational units (1 to n) that are interconnected in a specific manner in order to capture the spatial-temporal dynamics of one or more phenomena in a complex system. Each cell in a CCN layer is a computational node (Fig. 2) consisting of a communication unit, a computational unit and a learning unit. The communication unit is responsible for communication between cells in the same neighbourhood; the computational unit is responsible for performing computations on the input data to produce the desired output; and the learning/adaptation unit is responsible for dynamically adjusting the parameters of the computational unit in order to achieve the desired output.

The CCN can be implemented in a centralized or decentralized fashion. In other words, all the cells of the CCN can be spatially co-located in one central location, or the cells can be spatially distributed. A multi-processor platform at a data center is suitable for the former, whereas the latter requires a spatially distributed computing platform. In either case, the processors and platforms must communicate through at least one of several types of communication channels having different communication latencies.

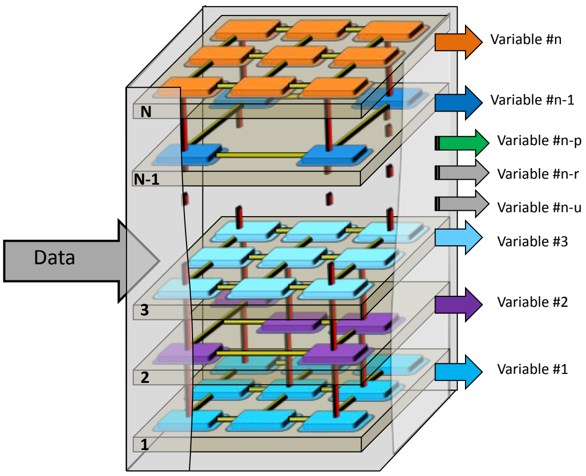

Fig. 1 A multi-layered (N) cellular computational network.

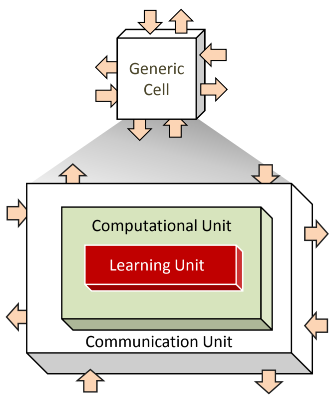

Fig. 2. Generic cell of a CCN consisting of three units: communication, computational and learning.

The computational units used in each of the cells can either be deterministic, as in a mathematical model, or heuristic, as in a neural network. The CCN cells can be homogeneous, meaning that only one kind of computational unit exists in the entire network, such as in a mathematical model, or heterogeneous, in which some of the computational units are mathematical models while some are neural network based. Furthermore, each mathematical model or neural network can be different.

The learning/adaptation unit must adapt the parameters of the computational unit using, for example, a backpropagation algorithm, if the computation unit is a feedforward multi-layered neural network (Werbos, 1994). In the case of recurrent neural networks, the learning algorithm can be backpropagated through time (Werbos, 1994). A special case of the CCN is a cellular neural network (Luitel and Venayagamoorthy, 2011; Luitel and Venayagamoorthy, 2012).

3. MODELING POWER SYSTEM DYNAMICS USING CCN

The CCN framework is unique because the power system's topology information is captured through the interconnections between the cells. The online dynamics of the power system are updated continuously with measurements made available through PMUs and other sensors, as illustrated in Fig. 3 for the IEEE68 test system with PMUs on all generator and other selected buses.

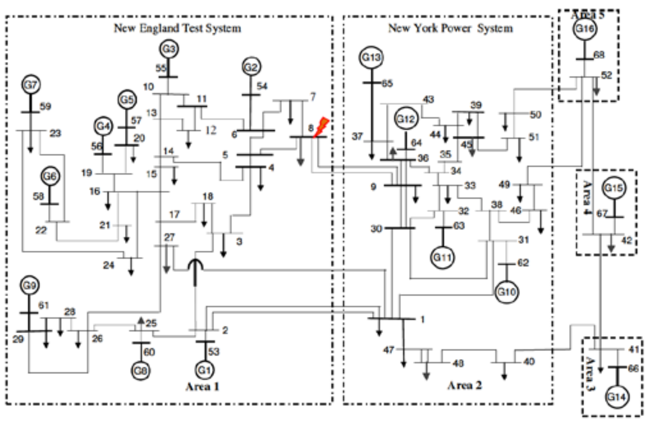

Fig. 3 New York-New England-IEEE 68 bus power system.

The power system is mapped using a CCN consisting of 16 cells for the *speedNet* (generator speed deviation prediction layer) and 68 cells for the *voltageNet* (bus voltage prediction layer). In a two-layered CCN consisting of two *statevarNets*, the inter-dependency of system variables in the actual system is represented by the interconnection of the cells across the *statevarNets*. Information is shared between the neighboring cells of different *statevarNets*. For example, the speed and voltage state variables can be coupled at the generator buses. Therefore, a cell that maps a generator bus in *voltageNet* and a cell that maps a generator in *speedNet* are connected and share information.

The CCN-based *speedNet* is shown in Fig. 4. The connectivity of the cells was determined by a sparse neighborhood matrix in which each generator was assumed to be connected to its *n* nearest neighbors. If each generator is connected to the two nearest generators, each cell will be connected to the other two cells. In systems with more than two generators, the electrical distance between the generators can be considered as the neighborhood criteria. The neighborhood size was chosen in order to allow full connectivity of the components and to avoid islanding of cells.

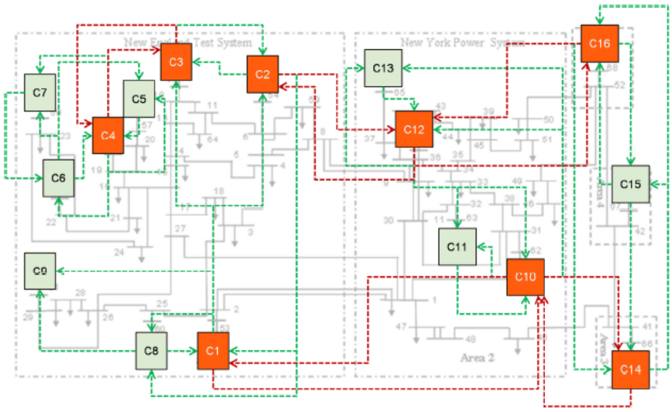

Fig. 4 *speedNet* for the IEEE 68 bus power system. The orange cells are connected with neighbourhood > 2, whereas the other cells have a neighbourhood = 2 (Luitel and Venayagamoorthy, 2012).

4. RESULTS AND DISCUSSIONS

4.1 CCN-Based Predictions

The typical speed deviations and voltages predicted/estimated using CCN appear in Figs. 5 and 6, respectively, for a 10-cycle, 3-phase line-to-ground fault on bus 8 (Fig. 3). Fig. 7 depicts a scatter plot with the coefficients of determination of all the cells in the *speedNet* and *voltageNet*. The plot shows results for light loading (base case) and heavy loading conditions. During heavy loading, the real and reactive powers of the loads in the base case increased by 20% and 5%, respectively.

4.2 Handling Loss of Data

Fig. 8 shows the connections to the cell that predicts the speed deviation of generator G10 based on the topology of the power system in Fig. 3 and its corresponding CCN-based modelling in Fig. 5.

Fig. 9 shows the results for a single-channel intermittent failure in the data input to cell C10. The PMU data transferred from generator G10 into cell C10 experienced intermittent failure during a 10-cycle, 3-phase short circuit for two seconds (20 samples at 100ms sampling rate). At a PMU data rate of 30 Hz, one in three PMU samples were streamed to the CCN. Due to cell C10's connectivity, the speed deviation estimation of generator G10 was still reasonable.

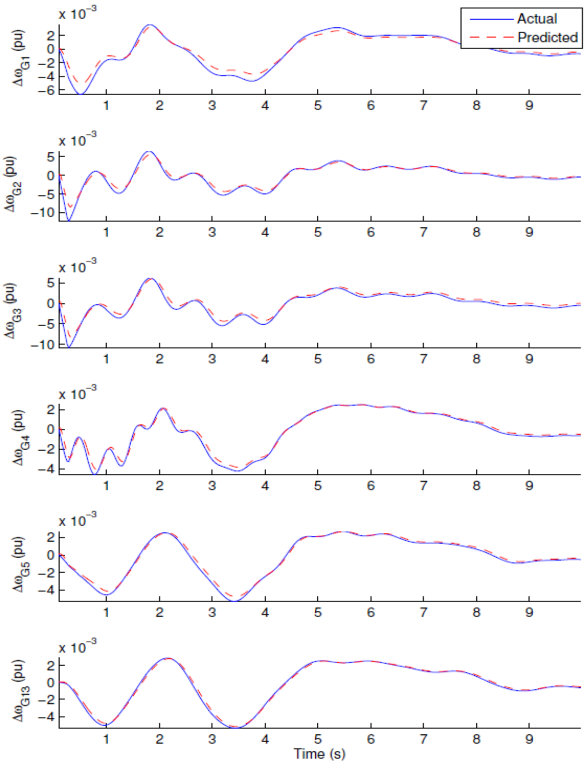

Fig. 5 CCN-based *speedNet* results of generator speed deviation predictions (G1, G2, G3, G11, G12 & G13 – Fig. 3).

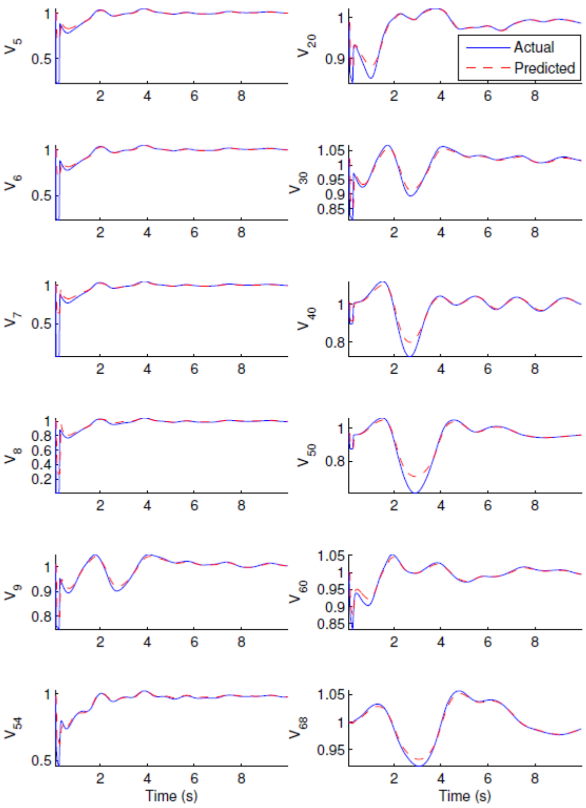

Fig. 6 CCN-based *voltageNet* results of bus voltage predictions (buses 5, 6, 7, 8, 9, 20, 30, 40, 54, 60 & 68).

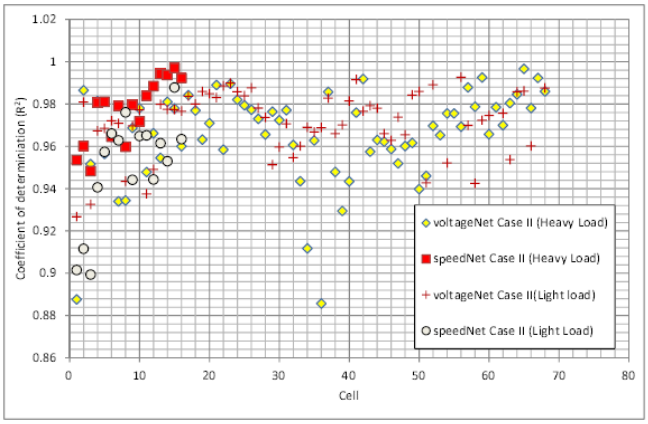

Fig. 7 Coefficients of determination of cell outputs of the two-layered CCN-based *speedNet* and *voltageNet*.

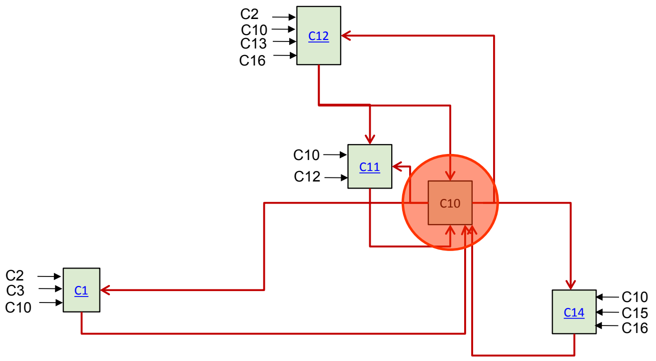

Fig. 8 Data links/connections to the cell (C10) modelling generator G10 dynamics. The data links are from the neighbouring generators (Gl, G11, G12, G14) and itself.

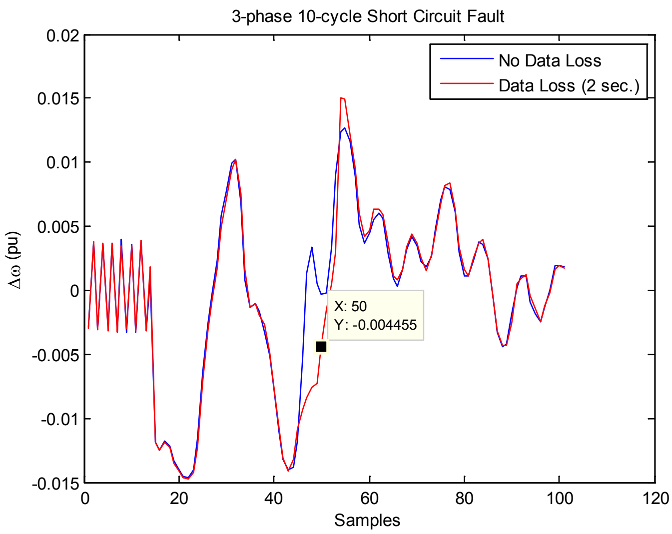

Fig. 9 Loss of generator G10 PMU data.

Figs. 10 through 13 show the prediction of the speed deviation of generators in the presence of multiple interacting bad data. The bad data occurred as a result of many multiple meter (PMU) failures lasting from 100 ms to 2 seconds.

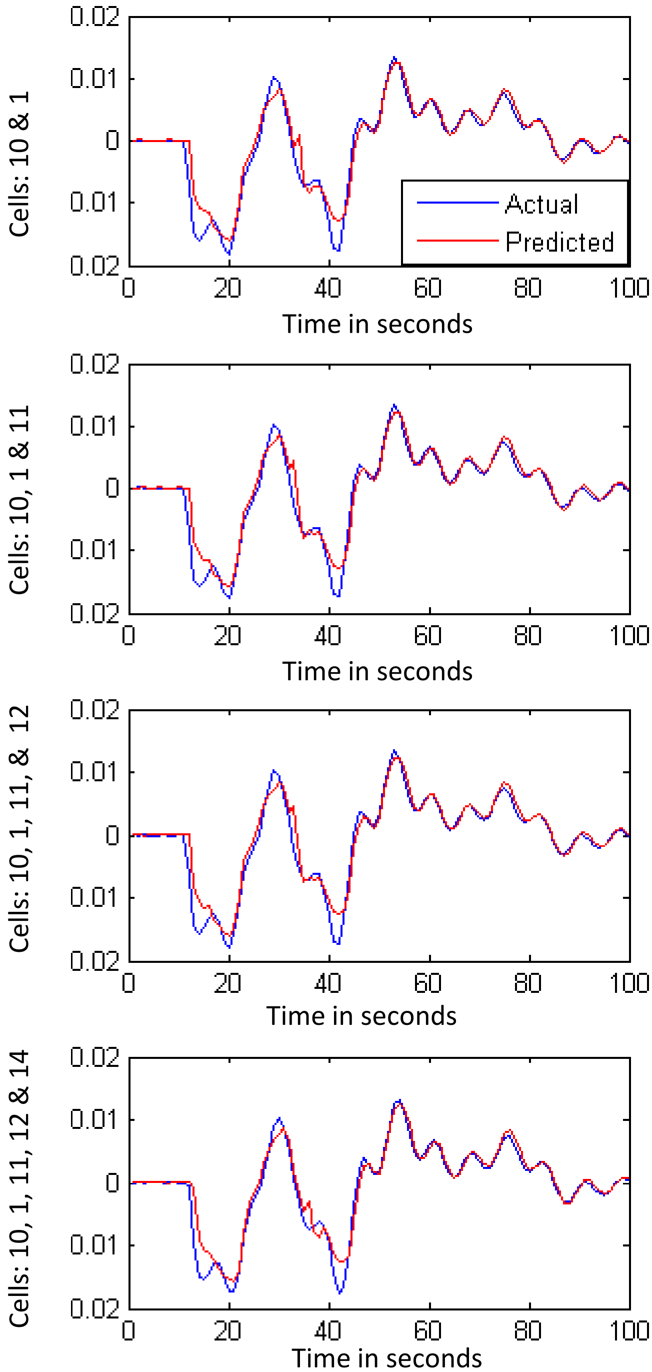

Fig. 10 Generator speed deviation prediction by the CCN-based *speedNet* with loss of data from one to five PMUs lasting 100 ms.

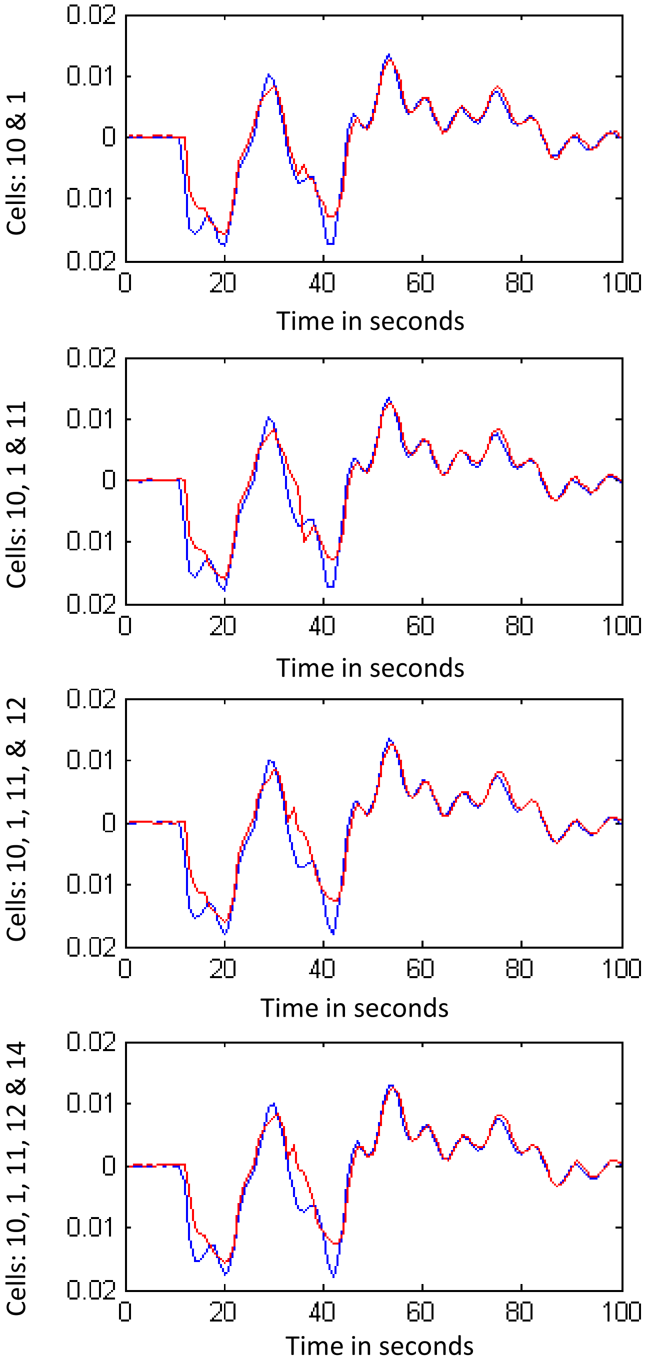

Fig. 11 Generator speed deviation prediction by the CCN-based *speedNet* with loss of data from one to five PMUs lasting 500 ms.

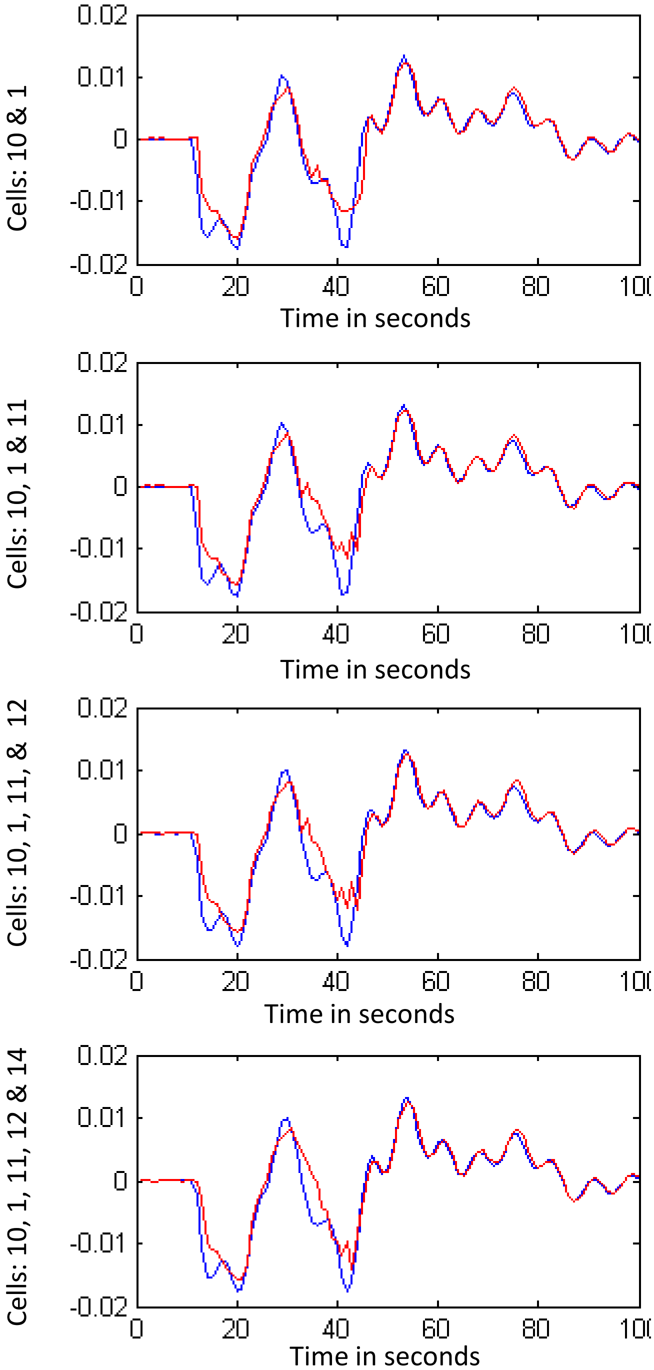

Fig. 12 Generator speed deviation prediction by the CCN-based *speedNet* with loss of data from one to five PMUs lasting 1 second.

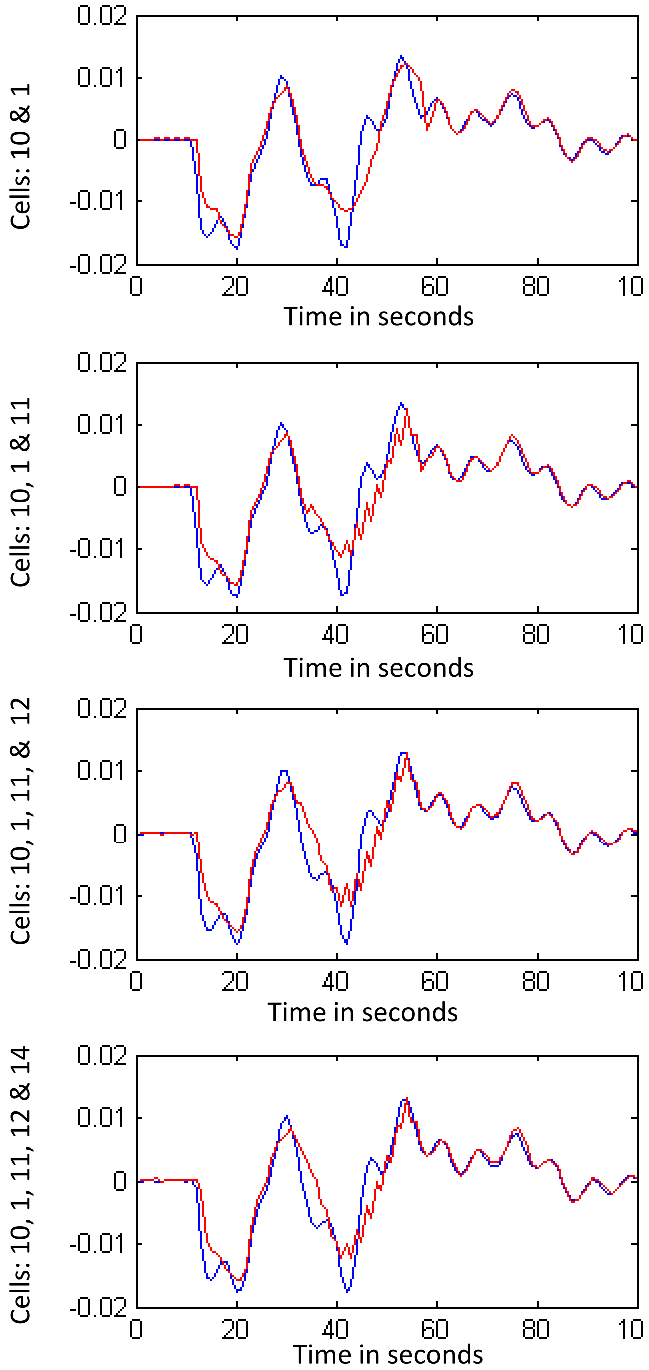

Fig. 13 Generator speed deviation prediction by the CCN-based *speedNet* with loss of data from one to five PMUs lasting 2 seconds.

Figs. 10 through 13 indicate that data loss did not severely degrade the prediction of the CCN-based *speedNet*. The same is observed with the *voltageNet* outputs. The CCN framework suppressed the propagation of bad data through its network.

5. CONCLUSIONS

A new intelligent framework known as the cellular computational network has been introduced for the predictive modelling and dynamic state estimation of power systems. This decentralized, nonlinear, computational approach is based on real-time data. The CCN-based DSE exhibited resilience to loss of single and multiple interacting and non-interacting data from one or more PMUs. Energy management system (EMS) applications could be executed in real-time with a high confidence level using the CCN-based dynamic state estimator. Ongoing research involves developing EMS applications based on CCN.

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